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What is in Local Dialects? A Field Experiment on Social Distance and Human Capital Development in Job Training

Sherry Xin Li [a], Shengzhe Wang [b], Shuo Yang [c,*]

[a] Department of Economics, University of Arkansas, Fayetteville, AR 72701, USA
[b] Institute for Studies in Country Development, Shandong University, No. 49 Zhenhua Street, Jimo, Qingdao, Shandong Province, P. R. China
[c] Department of Mathematical Economics and Finance, Economics and Management School, Wuhan University, Wuhan, Hubei Province, P. R. China, 430072

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ABSTRACT

This paper presents a field experiment at a large garment factory in China to investigate whether the reduced social distance between new sewing workers and their trainers affects the efficacy of on-the-job training. During the factory's new-worker training program, we randomly matched trainers and trainees based on whether they spoke the same dialects. We find that trainers voluntarily transfer more sewing techniques to trainees who speak the same dialects than to those who do not. This positive effect of shared dialects operates partially through non-work-related social closeness between trainers and trainees. Our results suggest that closer social distance could be cost-efficient leverage to reduce training costs and improve training outcomes.

1. Introduction

Human capital development is crucial for long-term economic growth (Nelson and Phelps, 1966; Barro, 1991; Hanushek and Kimko, 2000). Therefore, how workers acquire knowledge and skills through training and experience and how technological know-how spreads in the workplace are essential topics in economics. Numerous theoretical and empirical studies show that job training positively affects wages, productivity, and performances at both individual and organizational levels (Barrett and O'Connell, 2001; Balmaceda, 2005; Ballot et al., 2006; Tharenou et al., 2007). However, training costs can be forbiddingly high (Tharenou et al., 2007), and employers often must bear a significant fraction of these costs (Leuven et al., 2005). Therefore, providing high-quality job training within budget and enhancing employee productivity are among the challenges that corporations and organizations face. This study focuses on peer-to-peer training and investigates whether a relatively cost-efficient intervention—reducing the social distance between trainers and trainees—can be leveraged to help employers achieve employee-training goals and improve training efficacy.

Social distance, the perceived closeness between interacting individuals or groups (Kazdin, 2000), is an important concept in economics, management, psychology, sociology, and anthropology. Akerlof (1997) incorporates social distance as a key factor in economic modeling to explain decision-making. Research using experiments, mainly in the laboratory, in the past three decades shows that social distance plays a vital role in a wide range of economic decisions. Some studies manipulate social distance by varying the degree of the dictator's anonymity in the dictator game. They find that whether the dictators and the recipients interact anonymously affects the dictators' allocation decisions (Hoffman et al., 1996; Dufwenberg and Muren, 2002; Rankin, 2006). Some other studies find that social distance affects trust and trustworthiness. For example, closer social distance, categorized by pairing with an ingroup member in minimal groups, enhances trust and trustworthiness in the U.S., although its impact is different internationally (Buchan et al., 2006). People trust their fellow villagers (Etang et al., 2011), friends (Binzel and Fehr, 2013), or others whom they know (Brandts and Sola, 2010) more than strangers. They are more likely to select someone they are more familiar with than strangers to play a trust game, despite a lower rate of investment return (Fiedler et al., 2011). In addition, closer social distance is found to enhance cooperation

* Corresponding author.
E-mail addresses: SLi@walton.uark.edu (S.X. Li), szwang26@gmail.com (S. Wang), shuo.yang@whu.edu.cn (S. Yang).

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(Ahmed, 2007; Angerer et al., 2016) and reciprocity (Charness et al., 2007) and increase investment in riskier choices when profits can be shared with a paired friend (D'Exelle and Verschoor, 2015). Reduced social distance also discourages nonoptimal risk-taking on behalf of others (Montinari and Rancan, 2018) and facilitates team formation (Belot and van de Ven, 2011).[1]

More relevant to this paper, two field experiments find that closer social distance helps with knowledge transmission, although they both focus on non-workplace settings. Berg et al. (2019) find that without incentive pay, social distance impedes knowledge transmission of a public health insurance program in South India, but incentive pay offsets this negative effect by increasing the knowledge spreaders' effort. De Paola et al. (2019) show that being part of a socially connected team improves students' individual *and* team performances in an exam, suggesting that closer social distance could help alleviate free-riding problems and enhance knowledge spillovers among teammates.

Social distance also plays a vital role in interpersonal relationships in the workplace. Rotemberg (1994) introduces a theoretical model incorporating human relations into the workplace and shows that opportunities for workers to socialize can give rise to altruism toward fellow employees and consequently raise productivity. A growing number of field experiments demonstrate that social distance may improve or hamper productivity, and their effects may interact with monetary incentives. Bandiera et al. (2009) show that when paid fixed wages, managers favor workers socially connected to them regardless of the workers' productivity. But productivity-damaging favoritism disappears if managers receive performance bonuses. Park (2019) conducts a field experiment at a seafood-processing plant and shows that although workers value working next to friends, their productivity decreases if they work close enough with friends to socialize.

In addition to the experimental evidence, a related stream of non-experimental literature focuses on social ties with mixed findings. A social tie is "an affective weight attached by an individual to the well-being of another individual," which develops gradually through social interactions (van Winden et al., 2008; Goette et al., 2012). Studies show that social ties may help improve workers' productivity but may sometimes be detrimental to productivity. For example, Mas and Moretti (2009) find positive productivity spillovers generated by highly productive personnel. Such positive spillovers are greater for those who interact with the high-productivity workers more frequently than for those who do not. Bandiera et al. (2010) find that compared to working alongside coworkers with no social ties, a worker's productivity is significantly higher (or lower) when working alongside friends who are more (or less) able than her. They also show that the firm's distribution of worker ability yields an overall positive effect of social ties on aggregate performance. In contrast, Bandiera et al. (2005) find a negative impact of social ties, that is, workers exert *lower* effort under relative pay than individual pay to avoid negative spillovers to coworkers, especially with smaller group sizes or larger shares of close friends in their groups. Ashraf and Bandiera (2018) offer an excellent review of this literature.[2]

This paper adds to the literature by focusing on the impact of social distance on a vital contributor to productivity—on-the-job training. We present a field experiment at a large garment factory in China to examine whether and how closer social distance, through shared local dialects between trainers and trainees, may affect voluntary technique transfer and job training efficacy when monetary incentives for such transfer are lacking. We embedded this field experiment in the factory's annual training program for new sewing workers. In this one-on-one training program, the trainers receive a *fixed* pay rather than performance pay due to some practical considerations of the factory that we will detail in Section 3. With this fixed-pay system, how much to teach the trainees was entirely at their trainers' discretion. This setting allowed us to examine how reduced social distance, in the form of shared dialects, influences training outcomes such as the transfer of sewing techniques from trainers to trainees and trainees' post-training productivity in isolation of the potential influence of monetary incentives.

We took advantage of the diverse dialects that workers spoke and varied social distance by randomly assigning new sewing workers to their trainers in two treatments: trainers and trainees who shared the same dialects (the Dialect-Match treatment) and those who did not (the Dialect-Mismatch treatment). We then compared the number of sewing techniques that trainers voluntarily taught their trainees as well as trainees' post-training sewing performance and skills between these treatments. We find that dialects play an essential role in training efficacy. Specifically, trainers share significantly more sewing techniques with their trainees if they share the same dialects than if they do not. New workers can acquire these beneficial sewing techniques through extensive practice and experience, but self-guided learning takes time. Therefore, more techniques voluntarily transferred from trainers reveal their favoritism toward their same-dialect trainees. Our results also show that this positive impact of dialects is partially mediated through enhanced social closeness during off-work interactions between trainers and trainees. In addition, sharing the same dialects with their trainers leads to a qualitative increase in sewing productivity for trainees in their post-training test as well as significantly improved sewing skills when they join their respective sewing teams.

Our study contributes to the experimental literature on social distance and economic decision-making. Although the evidence based on lab experiments mainly shows a positive impact of reduced social distance on various prosocial behavior, a few field experiments yield mixed findings. Our focus is on the possible role of closer social distance in on-the-job training, an important but underexplored research topic in the previous literature. We show that the importance of reduced social distance, demonstrated in numerous lab experiments and some field experiments, can be leveraged to promote voluntary knowledge transfer and improve job training efficacy in the workplace without sufficient monetary incentives. Moreover, the focus of our study on the interactions between current workers and newcomers broadens the scope of a growing literature on social relations and workplace performance which examines hierarchical manager-worker or peer relationships (e.g., Bandiera et al., 2005, 2009). Its direct bearing on workplace mentoring also adds to the economic literature on mentoring more generally. For example, Goldhaber et al. (2020) find that having a productive mentor improves the productivity of mentee preservice teachers. While numerous studies document the positive effects of mentoring on schooling, behavioral, health, and job outcomes (Eby et al., 2007), our study offers a unique perspective on social distance between mentors and mentees, an essential ingredient of mentoring relationships underexplored in this literature. Last but not least, our study proposes a cost-efficient measure for managerial policymakers. Closer social distance can be leveraged as an influential nonmonetary factor that, if adequately incorporated, could promote a positive work environment and more effective sharing of information and resources and lead to

[1] Contrary to the literature above, a few studies find *no* impact of social distance, particularly on charitable donations (Brown et al., 2017; Gee et al., 2020).

[2] Other empirical research also shows that social ties affect other aspects of decision-making, e.g., editorial decisions to accept papers for journal publications (Laband and Piette, 1994), candidates' election probability to prestigious scholarly or political positions (Fisman et al., 2018; Fisman et al., 2020).

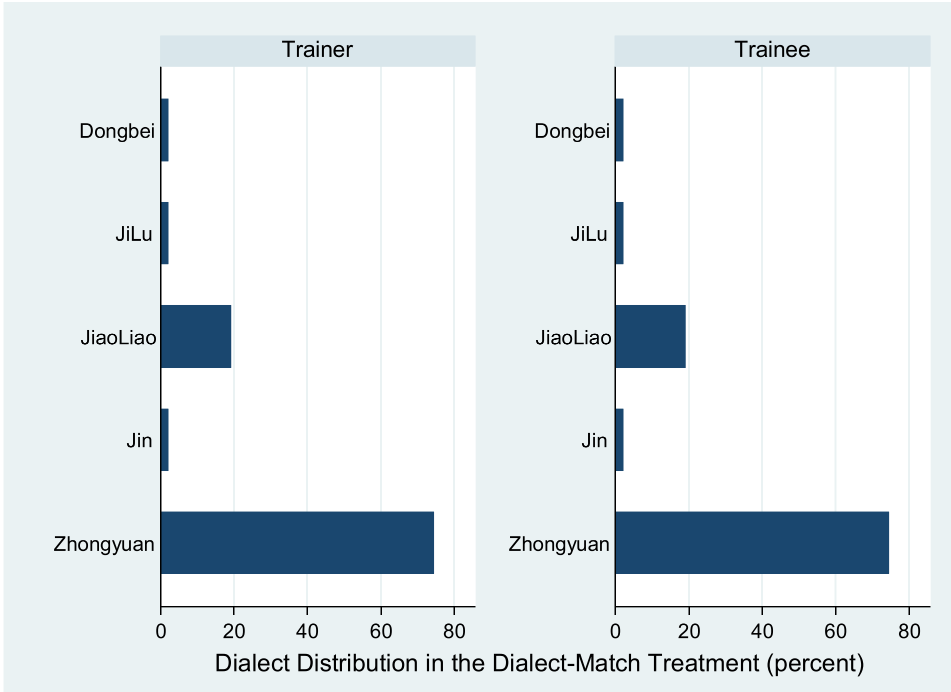

Fig. 1. Distributions of Dialects in the Dialect-Match Treatment.

better performance.[3]

We organize the remaining of the paper as follows. Section 2 provides a brief background on Chinese dialects. Section 3 explains the field setting and the experimental design. Section 4 introduces a conceptual framework and hypotheses. Section 5 presents the analyses and results. Section 6 concludes.

2. Background on Chinese Languages and Dialects

The official language of China is *Putonghua* or the Common Language based on Beijing Mandarin. However, many of the 1.398 billion population also speak their local dialects that linguists broadly categorize into different language supergroups, including Mandarin, Jin, Gan, Hui, Hakka, Min, Wu, Xiang, Yue, and Ping (Xiong and Zhang, 2012). Each of these supergroups can be further divided into different groups and further into various subgroups, as shown in the Chinese dialect family tree in Figure A1 of Appendix A. The dialects are relatively homogeneous in the north but much more heterogeneous in the south.

Among these supergroups, Mandarin is the most widely used and has eight dialect groups, including Beijing, Dongbei, Jilu, Zhongyuan, Jianghuai, Jiaoliao, Lanyin, and Xinan Mandarins. These dialects, often referred to as the northern language varieties, spread across the north and southwest, covering over three-fourths of the country (Ramsey, 2002). While dialects *within* each group are more similar relative to across these groups, the Mandarin dialects are overall mutually intelligible, although accents may differ. For instance, despite the considerable geographic distance—over 1,600 miles—between the city of Harbin in the northeast and the city of Chongqing in the southwest, which are situated at opposite ends of the Mandarin-speaking region, natives of these cities can converse with each other with relative ease (Ramsey, 2002). In contrast, the non-Mandarin dialects are much more diverse and make up one-fourth of the land in the southeast. Their differences are so vast that they are functionally different spoken languages and may be utterly unintelligible to one another.

The role of *Putonghua* was established as the official language following the success of the communist revolution in 1949 to unify the country's enormous dialect varieties. Since *Putonghua* is based on Beijing Mandarin, people from other Mandarin groups can learn it relatively easily, *albeit* with accents. However, promoting *Putonghua* in the south has taken considerable effort due to its drastic differences from the local dialects. Students learn *Putonghua* at school but use local dialects outside school since people around them speak local dialects in their daily lives. Nonetheless, *Putonghua* is an important tool when people participate in public life since it is used pervasively in governments and state-run media. Until 2020, about 81% of the Chinese population could speak *Putonghua* (Xinhua, 2021). In many situations, however, speaking local dialects is easier and necessary to reduce social distance with others who share the same dialects.

It is important to note that the term "dialect" differs from "accent." Accent refers to "manner of pronunciation" whereas dialect "covers the types and meanings of words available and the range of grammatical patterns into which they can be combined" (Laver, 1994, p. 55). A dialect can be expressed through written or spoken form. In the case of the spoken form, a particular dialect may be associated with more than one accent. For example, in our study, *Dongbei Mandarin* and *Putonghua* are two distinct dialects due to differences in vocabulary, grammatical patterns, and pronunciation. However, native *Dongbei Mandarin*

[3] Our study is also related to the literature on *guanxi*, which refers to social relationships between individuals (Yang, 1994) or personal connections (Chen and Chen, 2004) in Chinese society. *Guanxi* often stems from a recognizable foundation of social familiarity, such as shared birthplace, alma mater, or local dialect (as examined in our study), which facilitates the subsequent development of mutually beneficial relationships (Yang, 1994; Chen and Chen, 2004). According to Song et al. (2012, abstract), social distance is "reflected in the indigenous concept of *guanxi*" as a crucial aspect of Chinese culture. While some studies identify the negative ramifications of *guanxi* (e.g., Kung and Ma, 2018; Wang, 2016; Fisman et al., 2018), our study extends the list of economic settings in which *guanxi* can be efficiency-enhancing (e.g., Davies et al., 1995). We show that social relationships, such as shared dialects, can serve as a social lubricant, effectively reduce interpersonal barriers that impede *skills* and *knowledge transfer, and ultimately elevate collective human capital in the workplace.*

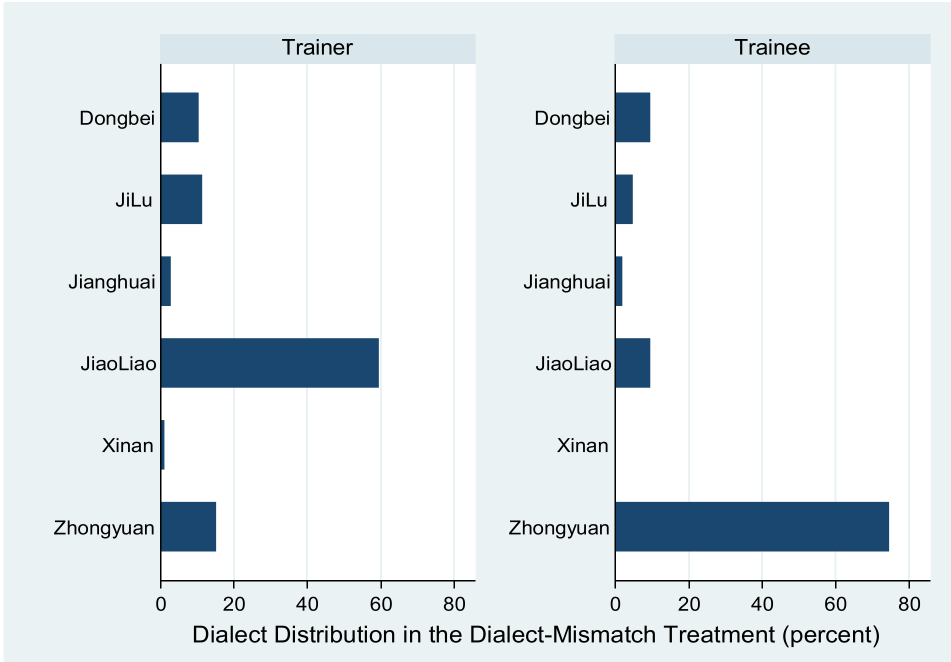

Fig. 2. Distributions of Dialects in the Dialect-Mismatch Treatment.

speakers can often speak *Putonghua* with little difficulty, albeit with a characteristic *Dongbei* accent. As *Putonghua* is the official language and taught in schools, many non-native speakers from almost all dialect groups can communicate in *Putonghua* with varying degrees of proficiency. These speakers often carry distinct accents that could sometimes be used to infer their geographic origin. Appendix A provides details on Chinese dialects, their differences from American dialects, and methods to quantify the dialect distance in previous studies.

3. Experimental Setting and Design

We conducted a field experiment at a large garment factory located in the suburbs of Qingdao in Shandong Province on the east coast of China, a hub for the apparel manufacturing industries. The factory is a subsidiary of a large apparel manufacturer of high-end sportswear, undergarments, and children's clothes that supplies premier garment brands in Japan, Western Europe, and North America. Workers at the factory comprise locals and migrants from other parts of Shandong Province and the country. To investigate the impact of dialects on the job training, we implemented an experiment consisting of two treatments—Dialect-Match and Dialect-Mismatch—depending on whether trainers and trainees spoke the same dialects or not.

In our sample, trainers and trainees belong to different dialectal groups of *Mandarin* except for one pair who speak *Jin*. Figs. 1 and 2 show the distributions of the dialects spoken by the trainees and trainers in each treatment.[4] Note that none of the trainers and trainees speak *Putonghua* as their first language. However, they could choose to speak *Putonghua* to each other if desired, particularly when they did not share any local dialects.

3.1. Factory Setting

We conducted the field experiment at the factory's sewing department as part of their regular training program for new workers. Each of the four sewing divisions was under a manager who supervised about a dozen production groups, each headed by a group leader. Each production group comprised about thirty workers who operated their sewing machines in two adjacent production lines across a 1.5-meter aisle. Regardless of gender and work experience, each worker was responsible for one sewing step (e.g., stitching corners, sewing the neck or sleeves) and paid a piece rate.[5] Next, she passed her finished items to the coworker sitting in front of her. A quality-control worker then examined the completed items at the front of the production line.

The factory recruited new workers from economically underdeveloped areas in Shandong or other provinces.[6] Most new workers had a middle school education. In our experiment, 36% of new sewing workers were male. The department managers and group leaders remained primarily female despite the recent increase of male workers in this historically female-dominated profession. The trainers must have at least three years of sewing experience.

3.2. Experimental Design

Our experimental design included a random pairing of trainers and trainees based on their dialects, a 20-minute training exit test to evaluate the trainees' learning outcome, and a post-experiment survey. We collected data from the second to the fourth week of February 2012 after new workers arrived in multiple cohorts at the factory after the Chinese New Year. The regular training program required by the factory consisted of one-day general orientation in groups and five-day one-on-one job-specific training with trainers at the sewing departments. Thus, our experiment started on Day 2 after their general group orientation and ended with the sewing test and the post-experiment survey on Day 6, as shown in the timeline in Fig. 3. One trainer was matched with only one trainee throughout the experiment. During the five-day job-specific training in which we embedded our experimental intervention, trainees

[4] We present more details on dialect matching on the pairing level in Appendix B.

[5] The factory used an advanced computer system to provide sewing workers instant feedback on their daily productivity. For example, after a worker processed a bundle of fabrics, she scanned and recorded it on a palm-pilot-size computer terminal attached to her sewing station to track her daily earnings.

[6] New workers in our sample came from seven provinces in China, including Shandong, Henan, Hebei, Heilongjiang, Jiangsu, Jilin, and Neimenggu.

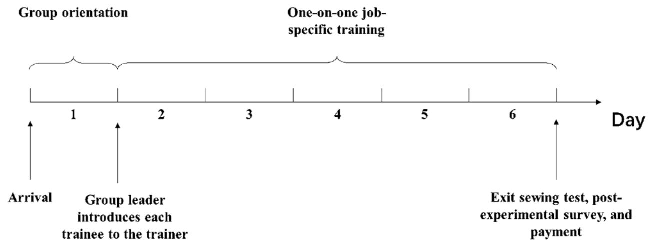

Fig. 3. Timeline of the Experiment.

Table 1
Variable Descriptions and Summary Statistics.

Variable name	Description	Mean (*N* =153)
Dialect-Match treatment	Experimental intervention: 1=Dialect-Match treatment, 0=Dialect-Mismatch treatment	0.307 (0.463)
Male trainer	Trainer is male (dummy variable)	0.085 (0.280)
Male trainee	Trainee is male (dummy variable)	0.359 (0.481)
Trainer age	Trainer's age	27.693 (9.251)
Trainee age	Trainee's age	21.641 (7.720)
Previous sewing experience	Did a trainee use a *family-style* sewing machine before training? (1=yes, 0=no)	0.170 (0.377)
Trainer's skill level	Trainer sewing skill evaluated by group leaders (1=not capable … 5=highly capable)	4.235 (0.676)
Level of communication barriers	Communication barriers between trainer and trainee (0=not at all … 3=a lot) (Survey Q6)	0.542 (0.607)
Offering trainees help outside work	Did the trainer offer the trainee any help outside work? (1=yes, 0=no) (Survey Q1) This variable is used to generate "social closeness score" in the median analysis (see details in Subsection 5.2)	0.203 (0.403)
Non-work-related conversations	How often did the trainers and trainees have conversations besides work? (1=never … 5=always). (Survey Q4). This variable is used to generate "social closeness score" in the median analysis (see details in section 5.2)	3.294 (1.006)

Notes: Standard deviations are reported in parentheses below the means. Our analyses control for the trainer-trainee age difference, as suggested by some readers, since it allows us to examine the age-based social distance. Replacing age difference by the trainers' and trainees' respective ages in the analyses does not impact our results, as illustrated in Appendix E.

learned serger (also called an overlock machine), the most used industrial sewing machine, with their assigned trainers.[7]

We collected trainees' personal demographic information, including gender, age, hometown, and dialect, upon their arrival. We stratified trainees by dialect to enable their random assignment to the Dialect-Match and Dialect-Mismatch treatments, aiming for a balance of each dialect between the treatments as much as possible. We also tried to balance trainee gender and age between the treatments if the subsample size of a particular dialect group permitted. However, achieving such balances was sometimes constrained due to small sizes of certain dialect groups.[8]

We then paired each trainee with a trainer, ensuring that each trainer-trainee pair shared the same local dialect in the Dialect-Match treatment, whereas each trainer-trainee pair spoke different dialects in the Dialect-Mismatch treatment.[9] The Dialect-Match treatment

Table 2
Trainers and Trainees' Characteristics by Treatment

Variables	Dialect-Match treatment (*N* = 47)	Dialect-Mismatch Treatment (*N* = 106)	*P-value*
Distribution of trainees' dialects	See Fig. 1	See Fig. 2	0.135 [a]
Male trainers (%)	14.89 (0.360)	5.66 (0.232)	0.059 [b]
Male trainees (%)	25.53 (0.441)	40.57 (0.493)	0.074 [b]
Trainer's age	23.81 (9.249)	29.42 (8.756)	<0.001 [d]
Trainee's age	19.89 (6.441)	22.42 (8.132)	0.112 [d]
Level of communication barriers	0.447 (0.583)	0.585 (0.615)	0.195 [c]
Trainee had previous experience using a family-style sewing machine (%)	17.02 (0.380)	16.98 (0.377)	0.995 [b]
Trainer's skill level	4.234 (0.633)	4.236 (0.698)	0.988 [c]
Offering trainees help outside work*	0.319 (0.471)	0.151 (0.360)	0.017 [b]
Non-work-related conversations*	3.660 (0.962)	3.132 (0.986)	0.003 [c]

Notes: See Table 1 for variable descriptions. Standard deviations are reported in parentheses.

* The two survey variables, "offering trainees help outside work" and "non-work-related conversations," are used to construct the *social closeness score* measure in the mediation analysis. The significant differences between the two treatments are the results of our randomization protocol, and thus are expected, i.e., trainers and trainees in the Dialect-Match treatment are socially closer and hence have higher values for both variables than those in the Dialect-Mismatch treatment.

[a] Fisher's exact test. See Figs. 1 and 2 for the dialect distributions for trainees and trainers in the two treatments.

[b] Test of proportions

[c] Test of means

[d] Test of medians. Used for skewed distributions (e.g., age)

[7] All newly recruited workers participated in our experiment with only two exceptions: a) experienced sewing workers recruited from other garment factories, and b) several workers assigned by the factory to train for more advanced sewing machines. Those in a) were waived from the sewing training in our study. Those in b) went through separate training, which was not a part of our experiment. Since both groups had a small number of workers and were excluded from our study *by the factory*, we never received any information about them. Therefore, from the research perspective, our study had no selection issue since all other new workers participated in our experiment.

[8] Since we did not have *all* the trainees' age information at the time of designing the randomization process due to their arrivals in different times, we categorized trainees into above- or below-median age groups based on their age and the median age of the factory's new workers from the previous year. Table 1 introduces all the variables used in the analyses.

[9] Specifically, we asked the factory managers to randomly assign ID numbers to trainers, who were current employees with at least three years of sewing experience and had volunteered to serve in the trainer role. We then implemented the following algorithm to randomly match a trainer to a trainee. For a randomly drawn trainee ID in the Dialect-Match treatment, we randomly selected a trainer ID. A dialect-match pair was formed if the trainee and trainer shared the same dialect. If not, we returned the trainer ID to the pool and randomly drew another trainer ID, repeating this process until a match was found. We performed this process for all the trainees in the Dialect-Match treatment. In addition, we carried out a similar process for each trainee in the Dialect-Mismatch treatment, ensuring each trainer-trainee pair was mismatched in their dialects. Due to the limited sample size and our objective to obtain enough same-dialect pairings for the Dialect-Match treatment, we were not in a position to stratify trainers according to their dialects, age, or gender prior to the random matching process. This limitation may likely result in imbalances across these dimensions.

consisted of 47 pairs, and the Dialect-Mismatch treatment 106 pairs, totaling 153 pairs in our experiment.[10] By design, Figs. 1 and 2 show no significant difference in the trainees' dialect distributions between the treatments ($p = 0.135$, Fisher's exact test); Figs. 1 and 2 show very similar dialect distributions between the trainers and trainees in the Dialect-Match treatment ($p = 1.000$) and drastically different distributions in the Dialect-Mismatch treatment by design ($p < 0.001$).

Since new workers arrived in multiple cohorts, no one could predict how many new workers would come eventually. However, the factory's management wanted to start training immediately upon each cohort's arrival. So we had to face the challenge of assigning new workers between the two treatments without being able to foresee the dialect and other demographic compositions of forthcoming new workers. Since the later cohorts came in smaller sizes, making it impossible to randomize based on their dialects *and* balance the age and gender distribution between the two treatments. So, we had to prioritize the randomization of trainees' dialects, but as the tradeoff, the overall sample was not very well balanced in terms of age ($p = 0.112$ for trainees and $p < 0.001$ for trainers, Table 2) or gender ($p = 0.074$ for trainees and 0.059 for trainers, Table 2) between the two treatments. Despite this limitation of implementing our stratified randomization in the field, all our analyses control for age and gender. They show that neither variable has statistically significant effects, and including or excluding them does not affect the results. In addition, the two treatments are balanced on other aspects, such as the level of communication barriers between trainers and trainees ($p = 0.195$), trainees' previous experience with family-style sewing machines ($p = 0.995$), and trainers' skill levels ($p = 0.988$).[11]

On the first day of job-specific training, the trainer's group leader escorted the assigned trainee to their sewing division and introduced the trainer and the trainee to each other, including their names, ages, and hometowns. The group leaders were blinded to our experimental design and uninvolved in the training process. Their only roles were to help with the logistics, i.e., escorting the trainees and introducing them to their trainers, and to assess the trainees' sewing skills after training.

Each sewing department was in an enormous building with high ceilings and large open work areas, with multiple production lines of workers working simultaneously. New worker training took place one-on-one with her trainer in a designated area on the opposite side, away from the trainer's workgroup in the open workspace. In general, the trainer would show the trainee around the department (e.g., where to find sewing supplies), introduce her to the sewing machine, and demonstrate sewing techniques. Then the trainer left the trainee to practice independently using fabric wastes in the training area. She may occasionally return to check in with the trainee for questions or to teach more sewing techniques. But since the trainer was expected to keep her own work going with her production group, it was entirely at her discretion how to allocate time between her work and helping the trainee. This process continued throughout the five-day job-specific training period.

Although it was not difficult to learn how to operate a serger, beginners could only acquire some highly beneficial, practical sewing techniques through tedious practices. Based on our interviews with ten group leaders, we gathered a list of effective sewing techniques summarized in Appendix C.[12] These techniques were not immediately apparent to beginners unless trainers were willing to share them during training. Unfortunately, trainers generally lacked strong motivations to do so since trainees' performance did not influence trainers' short-run compensation and long-run reputation at the factory for several reasons. First, to prevent trainers from cherry-picking more capable trainees, the factory, for several years before our experiment, had offered each trainer a *lump sum* of 200 yuan for each supervised trainee rather than performance-based pay. We adopted this lump-sum pay scheme not only because it suited our research need but also because the factory did not want us to surprise the workers by changing this pay scheme. Second, training new workers was not the trainers' only responsibility—they also needed to work on regular tasks with their teams during the training process. Third, some trainers may even be concerned about the hidden cost of creating potential competitions for themselves in the future in their group or department. Fortunately, the lack of sufficient monetary incentives for trainers in this setting provided a unique opportunity to study how *nonmonetary* factors, such as social distance between trainers and trainees, could influence voluntary technique sharing and training outcomes.

By the end of the fifth day, we conducted an exit sewing test to assess the trainee's progress.[13] The task was to make as many cloth widgets as possible by sewing together two pieces of 30cm × 7cm (11.8in × 27.6in) fabrics in 20 minutes. The reward was 30 cents for each widget that met the quality requirement. This test was conducted individually.[14] Before the training started, trainers and trainees were informed about the exit test without details.

We conducted a post-experiment survey (see the English translation in Appendix D) immediately after the sewing test to collect information on trainees' general experiences, interactions with their trainers, and the sewing techniques taught by the trainers. We phrased these survey questions so the workers could easily understand. Since most workers were unfamiliar with taking written surveys, the experimenter who spoke *Putonghua* read question-by-question to them and recorded their answers. When asking the trainees about the sewing techniques taught by their trainers, the experimenter read one piece at a time from the list (Appendix C), asked the trainees explicitly whether her or his trainer has taught this sewing technique during training. If the answer was affirmative, the experimenter proceeded to ask the trainees to demonstrate the technique on the sewing machine and recorded the number of sewing techniques that the trainees demonstrated correctly. This practice was designed to prevent potential biases in trainees' self-reported numbers. We told the trainees that we would not share their responses with anyone affiliated with the factory or company. After the survey, we gave them feedbacks on the test outcomes, including the number of widgets they made and the number that met the quality requirement during the test. They received payments in cash in sealed envelopes. It is important to note that the field experiment was integrated into the factory's standard new-worker training process, and the interactions between the experimenter and trainees occurred solely during the post-experimental survey. As a result, neither the trainers nor the trainees would be aware of their

[10] The sample size in Dialect-Mismatch treatment was bigger than the Dialect-Match treatment since our pilot experiment at a different factory showed that among the trainers and trainees with different dialects, some chose to speak *Putonghua*, and some spoke their respective dialects with each other.

[11] More discussions on communication barriers are included in Sections 4 and 5.

[12] We asked the group leaders to provide a comprehensive list of sewing techniques they deemed essential to improve a new worker's productivity. To verify the validity of this list, one coauthor went through the 5-day one-on-one sewing training with a trainer before our experiment started. His trainer was blinded to this list and the purpose of our study and did not serve as a trainer in the experiment.

[13] Since it was the factory's standard practice that a trainee joined the trainer's production group to work on actual products after the training, we were advised to conduct the exit sewing test by the end of the fifth day of the one-on-one training before the trainees started interacting with other experienced workers.

[14] Trainees were told in advance that their test performance would not affect their group assignment, future earnings, or their trainers' earnings. They were also told not to share the test details with others.

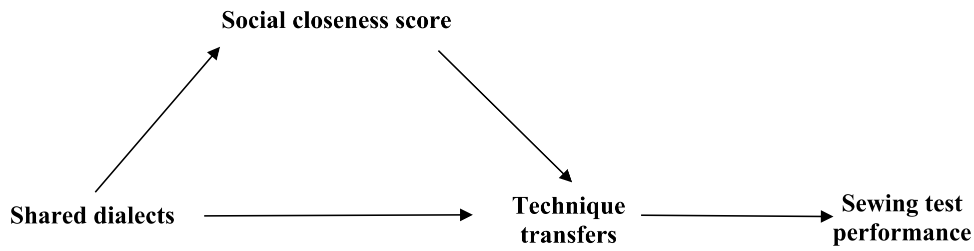

Fig. 4. A Conceptual Framework.

participation in a study until the survey was conducted.

4. Conceptual Framework and Hypotheses

We construct a conceptual framework depicted in Fig. 4, which serves as a roadmap for our analyses. This framework illustrates how shared local dialects affect sewing technique transfer, through what channel this effect may occur, and how dialects ultimately influence worker productivity.

As discussed in the introduction, social distance represents perceived closeness between interacting individuals or groups in broad economic settings. Our study focuses on a specific case of social distance based on linguistic dialects. Akerlof (1997) notes that "stable dialects for subgroups of the population … act as a diagnostic for social interaction" (p. 1015). Massey, Douglas and Nancy (1993) argue that social distance as reflected in the differences between the White and Black English dialects may attribute to the slow social integration in the United States. In China, with the vast land and ethnically homogeneous population, dialects often serve as a distinctive social marker for people to distinguish others who are like themselves from those who are not. Thus, when trainers and trainees, many being migrant workers, meet for the first time in our study, speaking the same dialects may serve as a salient cue to shorten their social distance. Since earlier literature indicates that reducing social distance leads to knowledge spillovers beneficial to others or teams (Berg et al., 2019; De Paola et al., 2019), we extend this finding to professional training in our setting and introduce Hypothesis 1 as follows.

Hypothesis 1. *Trainers are willing to voluntarily share more sewing techniques with trainees who speak the same local dialects than with those who do not.*

The impact of sharing the same dialects on technique transfer hypothesized above may operate through *reduced social distance* between trainers and trainees, thus giving rise to more altruism, as modeled theoretically in Rotemberg (1994) and supported by experimental evidence (e.g., Hoffman et al., 1996; Rankin, 2006; Bandiera et al., 2009). This increased altruism may manifest itself in trainers' utility function as altruistic trainers may care about their same-dialects trainees' learning outcome and future earnings, as previous studies show that closer social relationships (e.g., group or social identity) increase altruistic behavior (see surveys by Charness and Chen (2020) and Li (2020)). Altruism may also reduce the psychological cost associated with technique sharing, which a trainer may feel reluctant to incur with a socially distant trainee. For example, an outstanding trainee may generate negative spillovers by creating future competitions, and this (expected) concern may discourage a trainer from sharing techniques. But matching with a socially closer trainee may reduce such psychological costs for the trainer.[15] Although it is beyond the scope of our study to further differentiate these two potential mechanisms of altruism, either or both may be resulted from reduced social distance and consequently lead to more technique sharing between trainers and trainees.[16] This leads to Hypothesis 2.

Hypothesis 2. *Speaking the same dialects enhances social closeness between trainers and trainees, facilitating voluntary technique transfer.*

Technique transfer is essential in the workplace, as previous literature suggests that employer-provided job training enhances productivity (e.g., Bartel, 1994; Bishop, 1994; Black and Lynch, 1996; Barrett and O'Connell, 2001; Ballot et al., 2001, 2006; Tharenou et al., 2007; Liu and Lu, 2016). Therefore, we investigate the relationship between sewing technique transfer and trainees' productivity, as measured in the 20-minute exit test. Given that the list of these techniques was supplied by group leaders who considered them vital for improving a new worker's productivity, we expect that these techniques will boost trainees' post-training productivity. This leads to Hypothesis 3.

Hypothesis 3. *Trainees who acquire more sewing techniques during training will produce more good-quality products in the post-training sewing test.*

Hypotheses 1 and 3 suggest that shared local dialects may influence trainees' sewing productivity by facilitating the transfer of additional sewing techniques from trainers to their trainees. Our experimental design may help investigate this impact, i.e., the causal effect of shared local dialects on workers' productivity. We expect that trainees who speak the same dialects as their trainers will consequently exhibit enhanced post-training productivity, such as an increased production of good-quality products during the post-training test and elevated sewing skill levels assessed by group leaders when trainees join their respective sewing groups. This notion gives rise to Hypothesis 4.

Hypothesis 4. *Trainees who share the same local dialect with their trainers experience higher productivity and higher sewing skill levels.*

5. Empirical Analyses and Results

This section investigates how local dialects shared by trainers and trainees affect the voluntary transfer of sewing techniques from trainers to trainees and how this effect is mediated through reduced social distance between trainers and trainees. We also investigate to what extent the voluntary technique transfer relates to trainee productivity.

5.1. Effects of Dialects on Sewing Technique Transfer

One hundred fifty-three trainer-trainee pairs participated in the

[15] Early literature provides some supportive evidence. For example, Kato and Shu (2016) present an empirical study to show that in a Chinese textile firm, local workers and rural migrant workers compete aggressively with coworkers of a *different* social identity rather than with those of their same ilk.

[16] As discussed in Section 3, before the experiment started, we asked ten group leaders to provide a comprehensive list of sewing techniques essential for new workers to learn and make a smooth transition when they joined their production groups after completing training. Thus, it was common knowledge that these techniques could lead to positive learning outcomes and increase new workers' productivity and wages. Although we did not reveal this list to trainers to avoid the experimenter demand effect, we confirmed with the group leaders that the trainers knew what they were supposed to teach. To test the relevance of this list of sewing techniques, we have one coauthor go through the five-day sewing training with a trainer, the same process as all the trainees, before the experiment.

Table 3
Effects of Dialects on Technique Transferring (OLS)

	(1) Number of sewing techniques	(2) Number of sewing techniques	(3) Number of sewing techniques	(4) Number of sewing techniques
Dialect-Match treatment (β_1)	0.939***	1.033***	1.024***	1.083***
	(0.349)	(0.371)	(0.368)	(0.389)
Speaking *Putonghua* with similar accents (β_2)			0.292	0.206
			(0.493)	(0.518)
Speaking *Putonghua* with different accents (β_3)			0.195	0.106
			(0.372)	(0.384)
Trainers' skill level (β_4)		-0.068		-0.077
		(0.223)		(0.225)
Male trainer (β_5)		-0.204		-0.213
		(0.484)		(0.494)
Male trainee (β_6)		0.388		0.363
		(0.296)		(0.303)
Trainer-trainee age differences (β_7)		0.009		0.009
		(0.013)		(0.013)
Previous sewing experience (β_8)		0.183		0.165
		(0.330)		(0.336)
Level of communication barriers (β_9)		-0.021		-0.018
		(0.214)		(0.215)
Adj R^2	0.151	0.130	0.142	0.118
N	153	153	153	153

Notes: The dependent variable is the total number of techniques transferred from trainers to trainees. Columns (1) and (2) focus on the treatment effect on technique transfers, with the Dialect-Mismatch treatment in the omitted category. In Columns (3) and (4), we further differentiate the Dialect-Mismatch treatment into three subgroups, trainer-trainee pairs speaking *Putonghua* with similar accents, speaking *Putonghua* with different accents, and speaking *different dialects* (in the omitted category.) This enables us to compare technique transfers across these subgroups and the Dialect-Match treatment. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

experiment, with 91.5% female trainers and 64.1% female trainees. On average, trainers transferred 3.235 sewing techniques to trainees, and trainees produced 31 good-quality cloth widgets in the exit test. Among the 153 trainer-trainee pairs, 47 spoke the same dialects, and 106 did not.[17]

Table 2 presents trainers' and trainees' characteristics by treatment. Since the trainers and trainee never met before the training program, our experimental intervention of social distance is based on trainer-trainee dialect pairings—Dialect-Match or Dialect-Mismatch—randomly assigned in the experiment. Trainers and trainees developed relationships through interactions during training. The degree of their closeness is measured by their "social closeness score," which we will discuss in detail in Subsection 5.2. We assume that every trainee started with the zero sewing level with the *industrial* machines *ex ante* since none had any previous experiences with such devices, which was why they took the training. As an additional control measure, we elicited trainees' previous sewing experience using a *family-style* sewing machine and found no significant difference between the treatments ($p = 0.995$, test of proportions). Therefore, we could attribute the learning of industrial sewing (as quantified by the number of techniques trainers taught from Appendix C) to the training program or the trainers' knowledge sharing. Trainers' skill level, scaled from 1 (not capable) to 5 (highly capable), was evaluated by group leaders and showed no difference between the treatments ($p = 0.988$). In addition, we elicit a measure on the trainer-trainee communication barrier in the survey and find no significant difference between the treatments ($p = 0.195$). This lack of difference, despite different accents, is unsurprising. It could be due to the reasonably good intelligibility across the Mandarin dialectal groups and trainers' verbal instructions combined with sewing demonstrations during training. As explained in Section 3, since we needed to prioritize the randomization of trainer-trainee pairing based on their dialects, their gender and age compositions show some differences between treatments. Our regression analyses control for these variables as covariates. We control for the trainer-trainee age difference, as suggested by some readers since it allows us to examine the age-based social distance. Replacing their age difference by the trainers' and trainees' respective ages in the analyses does not impact our results, as illustrated in Appendix E.

Table 3 reports OLS regression results. The dependent variable is the number of sewing techniques that trainers teach trainees during training, measured by the number of correctly executed sewing techniques by each trainee during the post-experiment survey. The independent variable of interest is the Dialect-Match treatment dummy with the Dialect-Mismatch treatment omitted. In Column (2) of Table 3, we further control for trainers' and trainees' characteristics as listed in Table 1. One question on the impact of speaking the same dialect on technique sharing is whether this effect could be driven by reduced communication costs and lowered communication barriers between trainers and trainees. To address this question, we include an additional explanatory variable—the elicited communication barriers between trainers and trainees—in Column (2). This variable, scaled from 0 (no barriers) to 3 (very difficult to communicate), is based on trainees' self-report to Question 6 in the post-survey. Analyses in Table 3 and throughout the paper include the factory's sewing division fixed effects and trainers' and trainees' hometown fixed effects to control for the potential workplace and geographic areas' specific cultural effects. Results in Table 3 show that the trainers who speak the same dialects as their trainees share about one more sewing technique ($\beta_1 = 0.939$, $p = 0.008$ in Column (1); $\beta_1 = 1.033$, $p = 0.006$ in Column (2)), about 30% increase relative to the 3.198 sewing techniques transferred in the Dialect-Mismatch treatment. None of the other covariates statistically significantly impact the sewing techniques shared, and our result is

[17] In Question 5 of the post-experimental survey in Appendix D, we asked trainees whether they talked with their trainers in *Putonghua*, the same or different dialects. This question served two purposes. First, it helped verify our experimental intervention, i.e., those who self-reported speaking to their trainers in the same dialect were indeed those who were randomly assigned to the Dialect-Match treatment. In addition, the question gave us more information on how those randomized into the Dialect-Mismatch treatment communicated with their trainers. Among the 106 dialect-mismatched trainer-trainee pairs, 54 spoke *Putonghua*, and 52 spoke different dialects to each other.

robust with or without controlling for these covariates.[18,19] Result 1 summarizes this finding.

Result 1 (Effects of Dialects on Sewing Technique Transfer)

Trainers voluntarily transfer more sewing techniques to trainees who speak the same dialects than to trainees who do not.

Result 1 supports Hypothesis 1 and shows that speaking the same dialects substantially increases voluntary technique transfer. The level of communication barriers is an unimportant factor for technique transfer ($\beta_7 =$ -0.021, $p = 0.922$ in Column (2) of Table 3); including or excluding this variable has no impact on β_1, the coefficient estimate of the Dialect-Match treatment dummy. Therefore, the level of communication barriers is unlikely to drive the positive effect of speaking the same dialects on technique sharing.[20] In subsection 5.2, we will use a mediation test to investigate whether speaking the same dialects may shorten social distance between the new and experienced workers, stimulating voluntary sewing-skills transfer.

Our main analysis in the Columns (1) and (2) in Table 3 does not account for certain nuances in the languages. Specifically, among the 106 pairs of trainers and trainees in the Dialect-Mismatch treatment in the omitted category in Columns (1) and (2), 54 pairs spoke *Putonghua* (the Standard Form), and 52 pairs spoke different dialects, as indicated by trainees' responses in the post-experimental survey; those 54 pairs who spoke *Putonghua* to each other were likely to have accents given their overall educational backgrounds. This raises the question of whether trainers and trainees could deduce each other's geographic areas based on their *accents*, which would, in turn, affect technique sharing. In other words, do trainers share more sewing techniques with their dialect-matched trainees compared to the three subcategories previously nested within the omitted Dialect-Mismatch treatment in Columns (1) and (2)—speaking *Putonghua* with similar accents, speaking *Putonghua* with different accents, and speaking different dialects? Columns (3) and (4) in Table 3 address this question. It is worth noting that these three subcategories were not randomized, as it was the workers' choice to speak *Putonghua* (with similar or different accents) or different dialects in the Dialect-Mismatch treatment.

Since individuals from the same provinces often share very similar accents when speaking *Putonghua*, our analysis distinguishes *Putonghua*-speaking trainer-trainee pairs into those with similar accents (if from the same home province) or different accents (if from different home provinces). The trainer-trainee pairs who speak *different dialects* in the Dialect-Mismatch treatment are in the omitted category. Columns (3) and (4) show similar results, and the estimates of β_1 are comparable to those in Columns (1) and (2), demonstrating the robustness of Result 1. We also find no significant difference in sewing technique transfers between pairs with similar and different *Putonghua* accents ($\beta_2 = \beta_3$, $p = 0.871$, Column (4)), and neither subcategory is significantly different from those who share different dialects in the omitted category ($p = 0.692$ for β_2 and $p = 0.783$ for β_3). In addition, the impact of the Dialect-Match treatment is greater than those of similar *Putonghua* accents (β_1 vs. β_2, $p = 0.128$, Column (4)) or different accents (β_1 vs. β_3, $p = 0.050$), and the comparison between Dialect-Match and similar accents in *Putonghua* is not statistically significant due to the limited sample size. The weaker impact of similar or different accents in *Putonghua*, compared to Dialect-Match, on technique transfers suggests that speaking *Putonghua* may *not* effectively reduce people's social distance since, as *Putonghua*, the official language in China, is often used in more formal settings or when people do not share a local dialect.

5.2. Social Distance

To investigate to what extent social distance between trainers and trainees mediates the positive impact of shared dialect ties on voluntary technique transfer, we need a measure to quantify the degree of social distance between trainers and trainees. This measure should satisfy two criteria. First, it should represent the degree of social closeness between trainers and trainees. Second, it is preferable for this measure to be unrelated to work in order to minimize potential concerns about possible endogeneity that might arise from work-related interactions, if one believes that positive work-related interactions may be influenced by technique transfer from trainers to trainees. We apply these two criteria and identify useful information from two questions in the post-experiment survey (Appendix D). Question 1 asks trainees about the kinds of help their trainers offered, such as introducing machines and work procedures, showing them sewing techniques, giving them a tour around the factory, or helping them outside work. We can create an indicator variable of whether trainers offer their trainees any help *outside* work based on trainees' responses. Question 4 asks trainees how often they have non-work-related conversations with their trainers (scaled 1~5, with 1 representing never and 5 always). We use these two variables in principal-component factor analysis, with a varimax rotation, to derive a score for each trainer-trainee pair. These two variables load on a single factor with an eigenvalue of 1.193, the only eigenvalue higher than 1.[21] We call the resulting factor score *social closeness score* and use it as our measure to quantify the social distance between trainers and trainees in the mediation analysis below.[22] The higher the score, the closer the social distance.

We follow Baron and Kenny (1986) and conduct a serial mediation analysis in Table 4. The dependent variable of the mediation analysis is the number of sewing techniques trainers teach trainees during training. The mediator is the social closeness score between trainers and trainees

[18] One related question is whether technique transfer could potentially take place among *trainees* who share the same dialects. Our casual observations in the field suggested that this possibility was low for several reasons. First, most trainees were quiet, which was not unusual for these new workers. Their social interactions were primarily with their trainers. In addition, our experiment took place in four sewing departments in different buildings with multiple cohorts of new workers starting and ending their training at different times. The designated training areas were large, and trainees were spread far apart. Therefore, the likelihood of going through the same training stage in the same department with someone who spoke the same dialect was relatively low. To test this possibility empirically, we control for *each dialect group size* in Table F1 or control for each dialect group dummy in Table F2 in additional analyses. We find that spillovers among *trainees* are unlikely to be a driving force of technique transfer. Appendix F presents the details.

[19] Another question is whether certain dialect matchings work better than others in technique transfer. We rule out this possibility in Table F3 of Appendix F. In this analysis, we control for dialect dummies and further interact each with the Dialect-Match treatment dummy but find no differential treatment effects of these dialect groups.

[20] This result of communication barrier may be more suggestive than conclusive considering that our sample is composed predominantly of Mandarin dialect subgroups that are by and large mutually intelligible. Even mismatched dialect pairs can converse with each other with relative ease. Thus, it is not unexpected to see low average scores of communication barriers—0.447 out of 3 in the Dialect-Match treatment and 0.585 in the Dialect-Mismatch treatment ($p = 0.195$, Table 2), indicating a possible low variation in the communication barrier variable in our sample. It is also worth noting that any potential communication difficulty arising from varying dialects or accents can further be mitigated and are unlikely to hinder trainees' comprehension of their trainers during technique transfer because, in addition to verbal instructions, trainers also needed to demonstrate the techniques on sewing machines. Demonstrations are arguably more crucial than verbal instructions for manual tasks like sewing.

[21] The eigenvalue of the other factor is 0.8.

[22] We considered some other means (e.g., video recording or interviews with workers) that would allow us to directly observe or assess trainer-trainee communications and interactions. However, we decided against these approaches due to the difficulty of implementation because of the factory's policies and our concerns about experimenter demand effects.

that we construct above. The main independent variable is the Dialect-Match treatment dummy with the Dialect-Mismatch treatment omitted. Column (1) of Table 4 is identical to Column (2) of Table 3, showing that speaking the same dialects leads to an increase in the number of sewing techniques by 1.033 than those who do not (γ_1, $p = 0.006$). Column (2) indicates that if trainers and trainees speak the same dialects, the social closeness score increases by 0.638 (γ_1, $p = 0.014$)—a 0.69 standard deviation increase—compared to if they do not speak the same dialects. When the social closeness score (i.e., the mediator) is included in the regression of technique transfer in Column (3), the impact of the Dialect-Match dummy becomes 0.763 ($p = 0.039$), down from 1.033 in Column (1), whereas the coefficient of the mediator—social closeness score—is 0.423 and statistically significant ($p = 0.001$). Overall, the treatment effect of Dialect-Match falls by approximately 26.1% when we include social closeness score, the mediator, in the regression in Column (3). This mediation effect of social closeness score is sizable and statistically significant (Sobel test $p = 0.023$). It suggests that a part of the positive impact of the Dialect-Match treatment on technique transfer in Result 1 operates through the enhanced social closeness between trainers and trainees. We also observe that the communication barrier appears to reduce the social closeness score between trainers and trainees (-0.293, $p = 0.048$, Column (2) of Table 4). However, the direct impact of the communication barrier on the number of sewing techniques transferred is not significantly different from zero (Columns (1) and (3) of Table 4), regardless of whether we control for the social closeness score. Therefore, communication costs are unlikely to drive the treatment effect of dialects on technique transfer. These discussions lead to Result 2.

Result 2 (Mediating Effect of Social Distance)

The positive effect of trainers and trainees speaking the same dialects on sewing technique transfer is partially mediated through their enhanced social closeness.

Although our social closeness score, which is based on non-work-related relationships between trainers and trainees, does not directly capture their work-related connections, we cannot entirely dismiss the possibility of a correlation between work- and non-work-related relationships. This potential correlation might lead to some possible issues. For example, unobservable trainer characteristics (e.g., altruism), which may be correlated with both work- and non-work-related relationships, could naturally result in more sharing of sewing techniques. This argument would require a strong assumption that we had systematically and disproportionally assigned more altruistic trainers to the Dialect-Match treatment than to the Dialect-Mismatch treatment. We consider this possibility quite low, given our randomization process, albeit imperfect along the dimensions of dialects, age, and gender. As demonstrated in the analyses and appendices, our results remain robust after controlling for these covariates. Another possible issue related to the mediation test is that work- or non-work-related interactions or both may not be entirely exogeneous if a dialect match leads to more techniques transferred, consequently fostering closer trainer-trainee relationships on or off the job. While we acknowledge this as a potential issue, we believe it unlikely to entirely invalidate our mediation test, although we cannot completely exclude this alternative explanation given our experimental design.

Another question to consider is whether the positive (or negative) impact of the same (or different) dialects on technique transfer may result from the increased time needed to teach a sewing technique and hence a reduced number of techniques taught within a limited time frame, rather than less willingness to teach due to social distance. Although precise time measurements are unavailable, we believe that this channel is unlikely, given the high mutual intelligibility across Mandarin dialects (see Section 2) and the notably low communication barriers reported by trainees in the survey in both treatments (Table 2). In addition, the sewing techniques outlined in Appendix C consist of the fundamental skills. While it may take time for a novice worker to practice and attain proficiency, each technique in general does not require much time to teach. This is particularly true when a trainer, if willing to teach, also provides demonstrations alongside verbal instructions. Therefore, we anticipate minimal variation in the time required for trainers to teach these sewing techniques across the treatments. Even if a slight difference in time cost arises due to different dialects, this difference is likely to be negligible when compared to the entire duration of the five-day, one-on-one training process.

Result 2 supports Hypothesis 2. Results 1 and 2 indicate a gap in sharing sewing techniques in favor of the trainer-trainee pairs with matched dialects compared to those mismatched pairs.

Table 4
Mediation Test of Social Closeness Score on Technique Transferring

	(1) Number of sewing techniques	(2) Social closeness score	(3) Number of sewing techniques
Dialect-Match treatment (γ_1)	1.033***	0.638**	0.763**
	(0.371)	(0.255)	(0.365)
Social Closeness Score (γ_2)			0.423***
			(0.124)
Trainers' skill level (γ_3)	-0.068	0.062	-0.094
	(0.223)	(0.153)	(0.214)
Male trainer (γ_4)	-0.204	0.411	-0.378
	(0.484)	(0.333)	(0.468)
Male trainee (γ_5)	0.388	-0.129	0.443
	(0.296)	(0.203)	(0.284)
Trainer-trainee age differences (γ_6)	0.009	-0.007	0.012
	(0.013)	(0.009)	(0.013)
Previous sewing experience (γ_7)	0.183	0.004	0.181
	(0.330)	(0.227)	(0.317)
Level of communication barriers (γ_8)	-0.021	-0.293**	0.103
	(0.214)	(0.147)	(0.208)
Adj R^2	0.130	0.045	0.198
N	153	153	153

Notes: The dependent variables of the OLS analysis in this table are the total number of sewing techniques transferred from trainers to trainees in Columns (1) and (3) and social closeness score between trainers and trainees in Column (2). The Dialect-Mismatch treatment is in the omitted category. The variable "social closeness score" is constructed based on two items in the post-experiment survey: help received by trainees from their trainers in daily life and the frequency of non-work-related communication, using principal-component factor analysis (with a varimax rotation). The Sobel test confirms partial mediation ($z = 2.269$, $p = 0.023$). The total effect of the Dialect-Match treatment on shared sewing techniques is 1.033, 26% of which is mediated through social closeness score between trainers and trainees. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

5.3. *Trainee Sewing Performance in the Exit Test*

In Table 5, we investigate the relationship between trainees' productivity and the sewing techniques they acquire during training. The dependent variable of the OLS specifications in Columns (1) and (2) is the number of good-quality cloth widgets trainees produced in the training exit test; it is the *percentage* of good-quality widgets in Columns (3) and (4). The primary independent variable of interest is the number of sewing techniques trainees learned.

Column (1) shows that an additional sewing technique acquired by trainees is associated with increases in the number of good-quality cloth widgets by 1.035 ($p = 0.054$), which is 3.3% higher than the average number of 31.00 widgets these trainees made. When Column (2) further includes trainers' and trainees' characteristics, we obtain a similar estimate but with improved estimation precision ($\delta_1 = 1.088$, $p = 0.038$). In addition, more sewing techniques are also associated with a marginal increase in the *percentage* of good-quality widgets ($p = 0.076$ in Column (3) and $p = 0.084$ in Column (4)). Result 3 summarizes this finding.

Table 5
Effects of Sewing Techniques on Productivity (OLS)

	(1) Number of good-quality widgets	(2) Number of good-quality widgets	(3) Percentage of good-quality widgets	(4) Percentage of good-quality widgets
Number of sewing techniques (δ_1)	1.035*	1.088**	1.089*	1.080*
	(0.532)	(0.519)	(0.610)	(0.620)
Trainers' skill level (δ_2)		0.675		2.092
		(1.346)		(1.608)
Male trainer (δ_3)		0.695		1.801
		(2.914)		(3.481)
Male trainee (δ_4)		-4.899***		1.486
		(1.779)		(2.125)
Trainer-trainee age differences (δ_5)		-0.013		-0.022
		(0.079)		(0.095)
Previous sewing experience (δ_6)		2.735		1.228
		(1.988)		(2.375)
Level of communication barriers (δ_7)		-2.145*		1.067
		(1.251)		(1.494)
Adj R^2	0.027	0.088	0.071	0.055
N	153	153	153	153

Notes: The dependent variables are the number of good-quality widgets made by trainees in the exit test in Columns (1) and (2) and the percentages of good-quality widgets in Columns (3) and (4). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Result 3 (Sewing Techniques and Productivity)

Sewing techniques that trainees learn from trainers are associated with higher productivity.

Table 6 also reveals a positive relationship between social closeness score and trainees' productivity as measured in the numbers of good-quality widgets (1.864, $p = 0.013$, Column (1); 1.468, $p = 0.056$, Column (2)) although not in the percentages ($p = 0.873$ in Column (3) and $p = 0.909$ in Column (4)). Table 7 examines the impact of dialect match on trainees' productivity. The dependent variable is the number or the percentage of good-quality widgets trainees made in the exit test in Columns (1)-(4). Similarly, Table 8 presents the impact of dialect match on trainees' post-training sewing skill levels evaluated by group leaders. The results indicate that while the dialect match contributes to a *qualitative* increase in the number of good-quality widgets, the result is not statistically significant ($p = 0.201$ in Column (1) and $p = 0.557$ in Column (2) of Table 7). However, dialect match does significantly enhance trainees' sewing skills by 0.393 ($p = 0.015$, Column (1) of Table 8) or 0.419 ($p = 0.014$, Column (2)), out of a 5-point scale as evaluated by group leaders when trainees join their respective groups. Result 4 summarizes these findings which at least partially support Hypothesis 4.

Result 4 (Effects of Dialects on Productivity and Post-Training Sewing Skills)

Trainees who speak the same dialects with their trainers produce qualitatively more good-quality widgets in the post-training sewing test and have significantly higher post-training sewing skills than those who do not.

Table 6
Effects of Social Closeness Score on Productivity (OLS)

	(1) Number of good-quality widgets	(2) Number of good-quality widgets	(3) Percentage of good-quality widgets	(4) Percentage of good-quality widgets
Social closeness score (θ_1)	1.864**	1.468*	-0.139	-0.106
	(0.744)	(0.761)	(0.871)	(0.918)
Trainers' skill level (θ_2)		0.505		1.996
		(1.349)		(1.627)
Male trainer (θ_3)		-0.106		1.776
		(2.945)		(3.551)
Male trainee (θ_4)		-4.307**		1.771
		(1.783)		(2.150)
Trainer-trainee age differences (θ_5)		0.007		-0.015
		(0.080)		(0.096)
Previous sewing experience (θ_6)		2.912		1.326
		(1.993)		(2.403)
Level of communication barriers (θ_7)		-1.764		0.839
		(1.285)		(1.549)
Adj R^2	0.044	0.083	0.049	0.033
N	153	153	153	153

Notes: The dependent variables are the number of good-quality widgets made by trainees in the exit test in Columns (1) and (2) and the percentage of good-quality widgets in Columns (3) and (4). The variable social closeness score is constructed from two items in the post-experiment survey: help received by trainees from their trainers in daily life and the frequency of non-work-related communication, using principal-component factor analysis (with a varimax rotation). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 7
Effects of Dialects on Productivity (OLS)

	(1) Number of good-quality widgets	(2) Number of good-quality widgets	(3) Percentage of good-quality widgets	(4) Percentage of good-quality widgets
Dialect-Match treatment	2.855	1.344	-2.808	-2.347
	(2.221)	(2.280)	(2.545)	(2.705)
Trainers' skill level		0.606		1.933
		(1.368)		(1.623)
Male trainer		0.445		2.024
		(2.974)		(3.529)
Male trainee		-4.455**		1.551
		(1.815)		(2.154)
Trainer-trainee age differences		-0.003		-0.019
		(0.081)		(0.096)
Previous sewing experience		2.952		1.134
		(2.028)		(2.406)
Level of communication barriers		-2.135		0.534
		(1.311)		(1.555)
Adj R^2	0.012	0.059	0.057	0.038
N	153	153	153	153

Notes: This table is similar to Table 5, except that we replace the main independent variable—the *number of sewing techniques*—with the Dialect-Match treatment dummy. The dependent variables are the number of good-quality widgets made by trainees in Columns (1) and (2) and the percentages of good-quality widgets made in Columns (3) and (4). The Dialect-Mismatch treatment is in the omitted category. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 8
Effects of Dialects on Trainees' Post-Training Sewing Skill Levels (OLS)

	(1) Post-Training Sewing skill levels	(2) Post-Training Sewing skill levels
Dialect-Match treatment	0.393**	0.419**
	(0.159)	(0.168)
Trainers' skill level		0.035
		(0.101)
Male trainer		-0.080
		(0.219)
Male trainee		-0.150
		(0.134)
Trainer-trainee age differences		0.003
		(0.006)
Previous sewing experience		0.247
		(0.150)
Level of communication barriers		0.059
		(0.097)
Adj R^2	0.126	0.118
N	153	153

Notes: This table is similar to Table 7, except that the dependent variable is trainees' post-training sewing skill levels. The Dialect-Mismatch treatment is in the omitted category. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Two other factors that may potentially affect the trainer-trainee social distance and technique transfer are the same gender match and their home province tie. To examine these channels, we redo the analyses in Tables 3-8 by further controlling for these variables and report the results in Tables H1-H5 of Appendix H. Specifically, we include two additional dummy variables, one for the same-gender pairings and the other for same-home-province pairings. These two variables do not have any statistically significant effects in all five tables. The only exception is that in Table H2, the *same-gender pairing* positively impacts the social closeness score (0.878, $p = 0.030$, Column (2), Table H2).[23] Nevertheless, this effect of the same gender match does not affect other estimates in the mediation analysis. The Sobel test confirms partial mediation ($z = 2.009$, $p = 0.045$), indicating the total effect of the Dialect-Match treatment on shared sewing techniques is 1.183, i.e., 20.4% of the treatment effect is mediated through social closeness score between trainers and trainees. In addition, after we control for the same gender matching and home province pairing, the results do not change compared to those in Tables 3-8. These observations suggest that gender matching and home province ties are unlikely to drive our results.

6. Conclusion

In this paper, we present a field experiment at a garment factory in China to investigate how social distance, through shared dialects between trainers and trainees, affects the efficacy of job training in the workplace. We find that sharing the same dialects increases sewing techniques that trainers voluntarily transfer to their trainees relative to those who do not share such relations. We also find that this positive impact of sharing the same dialects operates partially through reduced social distance between trainers and trainees. In addition, when sharing the same dialects as their trainers, trainees experience a qualitative increase in sewing productivity during their post-training evaluations and display substantially better sewing skills when integrated into their respective sewing teams.

This study fills the gaps in the experimental economics literature on social distance and employee training and development—a critical determinant of the success of businesses worldwide. Our findings indicate that reduced social distance provides a valuable path for voluntary knowledge spillovers among employees, even without salient economic incentives. Upon training completion, new workers join the regular production teams. With extensive practice and cumulated experiences, the initial gap in their training outcome will likely diminish over time and eventually disappear. However, this fact should not veil some long-term benefits of good training outcomes. Good training outcomes substantially improve the onboarding experiences and bring new workers up to speed when they join their production teams. This is crucial for new workers since it boosts their confidence, social image, and working morale. It, in turn, helps increase job satisfaction and work engagement of new workers, build positive relationships among employees and retain promising talents for employers. Although beyond the scope of the present study, a valuable addition to the literature will be to investigate the impact of dialect match on job satisfaction and employee retention in future research, utilizing more comprehensive, long-term data when it becomes available.

Our study uses shared dialects as an example to show how organizations could leverage naturally occurring groups (e.g., gender, race, language, country of origin, and alma mater) to shorten social distance among employees in the workplace. However, we do *not* suggest that organizations rely exclusively on this approach since it may lead to possible divisiveness within organizations in the longer term. Instead, our findings have a broader implication. They suggest that successful strategies to shorten social distance among employees and build positive interpersonal relationships in the workplace must cultivate strong *non-work related social closeness* among their employees. To achieve this goal, organizations may promote a positive work environment by providing more opportunities for employees to socialize at work (e.g., open office spaces, gathering places such as a coffee lounge, and social hour gatherings; Holt-Lunstad, 2018). The mediation test in Result 2 shows that socialization does not have to be always work-related since the key to such interactions is building and strengthening a social relationship. Organizations may also consider socializing employees outside work (e.g., retreats, sports events). These opportunities in low-stress environments are excellent for networking, encouraging personal-level interactions, and improving communication and morale. Positive interpersonal relationships, at or outside work, may catalyze effective sharing of information and resources and encourage more altruistic and reciprocal behavior in the workplace.

Our evidence that reduced social distance, through shared dialects, facilitate voluntary technique transfers pertains to a specific kind of task (i.e., sewing) with a particular population (i.e., sewing workers with limited education). It will be interesting to investigate whether other social groups (e.g., race, gender, religion, and alma mater) may generate similar effects in human capital spillovers in the workplace, and whether such effects may apply to other professions with different workforces (e.g., a white-collar job with a well-educated workforce). We will leave these questions for future research. In addition, this paper extends a rapidly growing literature on social incentives (e.g., Bandiera et al., 2010; Ashraf and Bandiera, 2018). While our study highlights social incentives as a powerful motivator to facilitate voluntary skill sharing and human capital development, particularly in the absence of financial incentives, it is silent about the role of economic incentives due to the fixed-payment scheme preset by the factory. Fruitful future research can examine the interactions between social and monetary incentives in job training or workplace mentoring, the impact of other social incentives (e.g., reputation), externalities, and other long-term effects on individual performance and the organizations' performance as a whole.

Data availability

Data will be made available on request.

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Supplementary materials

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[23] The effect of this interaction term may not be accurately estimated due to a small number of observations.

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