DIVERSITY AND PRODUCTIVITY IN PRODUCTION TEAMS

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ABSTRACT

The popular press often touts workforce demographic diversity as profit enhancing because it may reduce the firm's communication costs with particular segments of customers or yield greater team problem-solving abilities. On the other hand, diversity also may raise communication costs within teams, thereby retarding problem solving and lowering productivity. Unfortunately, there is little empirical research that disentangles the above countervailing effects. Diversity in ability enhances the team productivity if there is significant mutual learning and collaboration within the team, while demographic diversity may harm productivity by making learning and peer pressure less effective and increasing team-member turnover. We evaluate these propositions using a novel panel data from a garment plant that shifted from individual piece rate to group piece rate production over three years. Because we observe individual productivity data, we are able to econometrically distinguish between the impacts of diversity in worker abilities and demographic diversity. Teams with more heterogeneous worker abilities are more productive at the plant. Holding the distribution of team ability constant, teams composed of only one ethnicity (Hispanic workers in our case) are more productive,

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but this finding does not hold for marginal changes in team composition. We find little evidence that workers prefer to be segregated; demographically diverse teams are no more likely to dissolve, holding team productivity (and hence pay) constant, than homogeneous teams.

Keywords: Teams; diversity; productivity; turnover; compensating differentials; collaborative skills

JEL classification: J3; D2; M12

INTRODUCTION

Workplace diversity is claimed to be one of the most important challenges facing managers today. Demographic trends, changing labor supply patterns, immigration, and increased globalization imply a much more heterogeneous group of employees for firms to manage. A number of firms and business executives have proposed a "business case" for diversity, which argues that a more diverse workforce is not necessarily a moral imperative, but is in fact a source of competitive advantage for two reasons. First, a more diverse customer base may be better served by a more diverse workforce that can effectively communicate with customer subgroups. Second, some assert that "diverse teams produce better results,"[1] arguing that heterogeneous team members will provide a broader range of ideas and potential solutions to a given problem.

Unfortunately, little research has empirically explored the business case for diversity.[2] The empirical research that does exist has found little support for it so far. Leonard, Levine, and Giuliano (2010), for example, examine the data from a chain of over 800 retail stores matched to census data on the demographics of each store's community and show that a store with workforce whose racial composition resembles that of the store's potential customers sells more but that the magnitude of the effect is too modest to be economically meaningful except when the customers do not speak English. The same paper also finds that, after accounting for the racial match between workforce and community, each store's racial composition has no significant impact on the store's productivity. Using the same data set, however, Leonard and Levine (2006b); Giuliano, Levine, and Leonard (2009); and Giuliano, Levine, and Leonard (2011), all find the own-race bias – unaccounted bias that favors counterparts in the same racial group as the decision-maker – in the decisions in hiring, exit, dismissal, and promotion. If these biases are caused by taste for discrimination, workplaces with higher racial/ethnic diversity will be more productive than more homogeneous workplaces.

In this chapter, we investigate the second claim that "diverse teams produce better results" in a production setting with a relatively simple technology. Key difference from prior research is that we identify a number of channels through which the team composition affects productivity, and we derive and test different theoretical implications for demographic and skill diversity.

Lazear (1998, 1999) asserts that a diverse team can generate productivity gains if three factors are present. First, team members must have different skills, ability, or information. In this way the team may gain from the complementarities among its members. Second, the different skills, ability, or information of team members must be relevant to one another. Obviously, little complementarity occurs if the skills of one team member are not relevant to the production of a teammate. Third, communication is necessary for team members to perform the relevant joint tasks and engage in knowledge transfer to enhance productivity. Increases in communication costs reduce the gains achievable from skill diversity. These factors suggest that at least two aspects of diversity should be considered when analyzing teams: (1) diversity in the skills, ability, and information sets of team members and (2) diversity in other factors that may enhance or inhibit within-team communication. Lazear's argument implies that productive teams should be diverse along the skills, ability, and information dimensions, but homogeneous in other dimensions, such as demographics, to reduce communication costs or what he calls "costs of cross-cultural dealing."[3]

The peer pressure model developed by Kandel and Lazear (1992) provides another framework to conceptualize the cost of diversity. They argue that profit sharing and the means to exert pressure are essential components for high productivity in teams. The means to exert pressure may include the capability to monitor each other and to punish shirkers or those who deviate from the team norm.[4] Partnerships among homogeneous workers are advantageous because mutual monitoring and social sanctions on deviators are more effective in such partnerships because demographic and skill homogeneity facilitate formation of a social norm and development of social ties. A number of authors including Reagans and Zuckerman (2001), Spagnolo (1999), and Towry (2003) emphasize the importance of social ties or social capital in encouraging cooperation in the workplace.

If workers in the same demographic group are more likely to belong to overlapping social networks, peer pressure may be more effective in mitigating free-riding because the implicit threat of breaking social ties will create peer pressure, thus providing incentives. Finally, Bandiera, Barankay, and Rasul (2005) emphasize the importance of worker preferences in determining whether group incentive schemes outperform individual piece rates.[5]

While workers may prefer more demographically homogeneous groups in order to reduce communication costs and increase productivity and pay, Becker's (1957) model of co-worker discrimination suggests that demographically diverse teams also may reduce worker utility. If workers are prejudiced, they may choose to segregate themselves within the workplace and form teams with similar individuals even if these teams generate less pay for their members. Consequently, Becker's model implies that increasing demographic diversity within teams at the firm may increase turnover if employees have preferences for working with similar individuals.

We provide a theoretical framework that allows us to jointly analyze the impacts of both skill diversity and demographic diversity on productivity and team member turnover in a production setting. First, we confirm Lazear's argument that output is higher when there are benefits of collaboration and significant skill diversity. Second, we identify three paths through which demographic diversity affects productivity and turnover: (1) diversity could inhibit knowledge transfer among team members, (2) diversity could reduce peer pressure by weakening social ties and trust among team members, and (3) "tastes for discrimination" create non-pecuniary disutility of joining or remaining on a demographically diverse team. These three paths collectively imply that demographic differences should harm team productivity and raise team-member turnover.

Empirical analysis of the relationship between diversity, productivity, and turnover in teams faces many challenges. Demographic characteristics may be correlated with worker skill. While characteristics such as age and race are typically collected in most data sets, worker abilities and productivities generally are not. Research in organizational behavior on team diversity typically relies on cross-sectional surveys that generate self-reported qualitative measures of team performance, which are problematic for identifying skill and performance due to self-reporting biases. Consequently, it is difficult to empirically separate the role of skill diversity from communication costs induced by demographic diversity in teams.[6] To the extent that the level of certain skills and knowledge sets that are complementary with each other vary across different demographic groups, there may be observed gains from demographic diversity in some contexts.[7]

Moreover, team membership over time often is not available. Researchers then are forced to examine the role of demographic heterogeneity at the firm or establishment level. However, diversity at the establishment level may mask substantial segregation among teams within a particular location, which will bias productivity and turnover estimates.[8] In addition, more diverse plants or firms may differ in other ways that are not observed by the econometrician, but which also affect productivity and turnover, contaminating estimates of the impact of diversity.

Our approach to the empirical analysis of diversity in teams attempts to address these issues by utilizing a novel data set consisting of the personnel records of workers employed between 1995 and 1997 at a garment factory operated in Napa, California, by the Koret Company, first studied by Hamilton, Nickerson, and Owan (2003) (henceforth HNO). The facility initially used progressive bundling system production, in which sewing is divided into independent tasks and seamstresses are paid piece rates. Between 1995 and 1997, the facility changed the organization of its sewing activity to module production, in which autonomous work teams of typically six to seven workers receive a group piece rate and perform all sewing tasks.

The advantage of our data set is threefold. First, teams are autonomous in deciding on how to assign and coordinate on tasks – thus knowledge sharing is critical for improving productivity – and they are the work units where most interactions among employees take place. Therefore, if workplace diversity affects the productivity through its impacts on communication, learning, or peer pressure effectiveness, our data provides an appropriate unit of observation. Second, because we observe productivity in individual piece rate production for almost all workers that eventually join a team, we are able to construct measures of both the skill level and the skill diversity for each team. We are therefore able to distinguish between the roles of skill and communication costs, as measured by team demographics, on productivity and turnover.[9] Third, because we focus on teams operating side-by-side within the same factory, our results are not biased by other variations in human resource practices across plants or across tasks that may bias the results of other studies.

Our findings are largely consistent with the predictions of our formal model. First, teams more heterogeneous in worker abilities are more productive, indicating that there is significant mutual learning and task coordination within the team. Second, holding the distribution of team ability constant, teams composed only of one ethnicity (Hispanic workers in our case) are more productive, but this effect becomes insignificant when team fixed effects are included in the model. The fixed effects estimates also show that marginal changes in team composition (i.e., the replacement of a single worker on the team) that lead to increased skill diversity continue to significantly improve team productivity. Finally, diversity has a low turnover cost at Koret. Teams that are more productive (and hence receive higher pay) are more likely to remain intact. Controlling for team productivity, demographic diversity does not significantly influence team turnover, suggesting that workers do not have strong preferences for segregation. Similarly, peer pressure does not appear to be strong enough to induce the least able team member to switch teams or leave the firm.

THEORETICAL BACKGROUND

We explore the relationships between various types of diversity and team performance and turnover by using a simple model of knowledge sharing and task coordination and a model of peer pressure à la Kandel and Lazear (1992). These models, along with Becker's (1957) model of co-worker tastes for discrimination, capture the consequences of diversity in skills and demographic characteristics on productivity and turnover relevant to team production in the context of the garment factory we analyze.[10] We use these models to derive empirical implications.

A Model of Task Coordination and Knowledge Sharing

HNO (2003) argues that two kinds of learning are promoted by teams at Koret – collective and mutual learning – which can be viewed as optimization of the production process and knowledge sharing. Teams facilitate the discovery of new ways to assign, organize, and perhaps alter tasks to produce more efficiently by putting together the teammates' idiosyncratic information. But at the same time, technical abilities often spread from more skilled workers to the less skilled ones. Workers learn how to execute tasks better and more quickly from one another.

Suppose there are N heterogeneous workers indexed by i and N heterogeneous tasks indexed by k. Each worker encounters one problem in carrying out her task and workers differ in problem-solving abilities. Let λ_i be the probability that the solution worker i devised for her problem is correct. Tasks also differ in opportunities for productivity improvement. Assume that each worker produces output $1 + d_k$ when she implements a right solution for the problem in performing task k and 1 when she does not. Therefore, d_k is the productivity gain achieved by solving the problem for task k. Let y_{ik} be the productivity of worker i who is assigned task k. Then,

$$y_{ik} = \begin{cases} 1 + d_k \text{ with probability } \lambda_i \\ 1 \text{ with probability } 1 - \lambda_i \end{cases} \tag{1}$$

Without loss of generality, assume $\lambda_1 < \lambda_2 < \cdots < \lambda_N$ and $d_1 < d_2 < \cdots < d_N$. Let $\bar{\lambda} = mean(\lambda_i)$ and $\bar{d} = mean(d_k)$.

We assume that a worker cannot learn whether she has successfully solved her problem until the production is complete. Workers can improve the quality of their solutions by getting help from others. Let h_{ij} be the communication cost between worker i and worker j, the share of available production time spent by both workers to communicate the problem and its solution, instead of producing garments. In other words, h_{ij} is the lost production time to transfer knowledge between worker i and worker j. To simplify our argument, assume knowledge is perfectly substitutable and more skilled workers know everything that less skilled ones know. Namely, if $\lambda_i < \lambda_j$, worker j can improve the probability of success by $\lambda_j - \lambda_i$. When this perfect substitution assumption holds, we can show that a worker does not ask more than one teammate for help. Therefore, when worker i asks worker j for help, their expected productivities, conditional on no other worker asking worker j for help, are $y_{ik} = (1 - h_{ij})(1 + \lambda_j d_k)$ and $y_{jl} = (1 - h_{ij})(1 + \lambda_j d_l)$, respectively.

Now let us explain the role of team production in the context of the garment factory we analyze using this model. In the progressive bundling (individual production) system where workers receive individual piece rates, there will be no knowledge sharing among workers because able workers get nothing by bearing the communication cost to teach less able workers. Also, assume that the d_k's are the private information of workers. In other words, workers learn from their experience with one another how to assign tasks efficiently whereas supervisors do not learn such information. Hence, supervisors randomly assign tasks to workers.[11] In this case, the total productivity in the progressive bundling system is

$$Y = \sum_{i=1}^{N} \underset{k}{E}\, y_{ik} = N + \sum_{i=1}^{N} \lambda_i \bar{d} = N(1 + \bar{\lambda}\bar{d}) \tag{2}$$

In the module (team) production system, where teammates receive the team piece rate, workers try to allocate tasks efficiently using their private information. This task coordination alone would improve efficiency because, even without knowledge sharing to solve problems, a team of N workers will achieve the productivity:

$$Y = \sum_{i=1}^{N} y_{ii} = N + \sum_{i=1}^{N} \lambda_i d_i > N(1 + \bar{\lambda}\bar{d}) \tag{3}$$

In addition, the team should benefit from knowledge sharing. Worker i, who cannot find a solution for her problem, can increase team output by asking worker j for help if

$$\underbrace{(1 - h_{ij})(1 + \lambda_j d_i) - (1 + \lambda_i d_i)}_{\text{Worker } i\text{'s productivity gain when asking } j \text{ for help}} - \underbrace{h_{ij}(1 + \lambda_j d_j)}_{\text{Worker } j\text{'s opportunity cost}} > 0$$

There is no conflict of interest between i and j because no personal cost is assumed here and output-based pay to the group is equally shared among its members. A worker may not always ask for help when she cannot solve her problem if the communication cost is too high. When she does ask for help, she may not always ask the most productive worker N. This is because worker N's opportunity cost will be very high if d_N is much greater than other tasks.

Now the production function for the team of N workers is

$$Y = N + \sum_{i=1}^{N} \lambda_i d_i + \sum_{i=1}^{N} \max_{j>i}[\max\{(1 - h_{ij})(\lambda_j - \lambda_i)d_i - h_{ij}(2 + \lambda_i d_i + \lambda_j d_j), 0\}] \tag{4}$$

We state two basic results for the model:

1. When the team's $\{d_i\}$ and $\{h_{ij}\}$ are sufficiently homogeneous or the $\{h_{ij}\}$ are close to zero, a mean-preserving increase in the variance of λ_i never lowers team productivity. When $N = 2$, the team productivity is always non-decreasing in λ_2–λ_1.
2. An increase in h_{ij} reduces the team productivity for any (i, j).

More formal presentation of the results and their proofs are in Appendix A.

The first result indicates that the gain from knowledge sharing and task coordination is increasing in skill diversity. Furthermore, this relationship is more apparent when communication costs are low enough so that knowledge sharing is maximized, suggesting complementarity between skill diversity and low communication costs.[12] Knowledge transfer becomes more frequent and effective as the difference in skill and knowledge rises and communication costs decline. The reason we cannot generalize this result to more heterogeneous tasks and communication costs is that workers may not always ask the most able teammate for help, since the opportunity costs of knowledge sharing for the most productive workers increases as skill diversity rises due to task coordination. If knowledge flows less from the top as skill diversity increases, it does not necessarily raise team productivity for all patterns of an increase in skill dispersion. However, as we illustrate in numerical examples included in Appendix B, the appearance of such non-monotonicity is quite limited and the trend shows a positive correlation between skill diversity and team productivity.

The second result shows that an increase in communication costs always negatively affects team productivity. If demographic diversity hinders communication among workers, it should lower team productivity on average.

Models of Peer Pressure

Next, we discuss the possible role of peer monitoring and peer pressure in team production. Kandel and Lazear (1992) argue that peer pressure arises when individuals deviate from a well-established team norm. Let $e = \{e_1, ..., e_N\}$ be the profile of efforts made by teammates and $Y(e)$ be team output (pay) that is equally shared among them. Worker i's payoff is

$$\frac{Y(e)}{N} - c_i(e_i) - P(\bar{e} - e_i) \tag{5}$$

where $c_i(e_i)$ is the cost of effort and $P(\bar{e} - e_i)$ is the peer pressure function that takes a greater value as worker i works less than the team norm $\bar{e}$. So $P' > 0$ for $e_i \leq \bar{e}$. For example, suppose $P(\bar{e} - e_i) = \gamma \max\{\bar{e} - e_i, 0\}$ and $\bar{e}$ is the expected average effort level (i.e., in the equilibrium, $\bar{e} \equiv (1/N)\sum_{j=1}^{N} e_j^*$ where e_j^* is the equilibrium effort choice by worker j). Then, the equilibrium is uniquely determined and each worker's choice of effort is an increasing function of γ. Some workers may choose $e_j^* < \bar{e}$ and bear peer pressure if her marginal cost of effort is too high. Bandiera, Barankay, and Rasul (2010) have shown that the conformism to a social productivity norm arises when workers work side-by-side with their friends.[13] In accordance with their finding, we argue that γ is determined by the strength of social ties among team members. The penalty imposed on deviating teammates is disutility from terminating their social relationship or receiving mere threat of doing so. If homogeneity in demographic background plays an important role in developing social ties among team members (Towry, 2003), diversity in the demographic dimensions should lower team productivity by weakening the social ties among team members and reducing the cost of shirking.

Impact on Turnover

The knowledge-sharing model described above implies that skill diversity should have a positive impact and demographic diversity a negative impact on worker earnings in the team if pay solely depends on the team output and is equally divided. The Kandel and Lazear (1992) model also suggests that demographic diversity may reduce worker earnings if the social bond among team members weakens, which then reduces the impact of peer pressure on productivity. In these models, skill (demographic) diversity works to reduce (increase) turnover through the impact of these factors on productivity and hence pay.

Diversity, however, may also directly influence the non-pecuniary benefits and costs of team participation. For example, as skill diversity increases, the team norm may become prohibitively high for the least productive worker even when her pay increases. If workers have "tastes for discrimination" as in Becker (1957), participating in a demographically homogeneous team increases individual utility. The Becker model has two implications for team formation and turnover. First, one would expect workers to form ethnically or age segregated teams, even in the absence of a productivity effect. Second, if individuals are prejudiced, increased demographic diversity on teams should be associated with higher individual turnover, holding pay constant.

Finally, we note that workers may differ in their options outside the team. For example, if the outside option value is increasing in worker skill, the most productive worker may find it optimal to switch to another team or take a job at some other firm as the skill gap between her and her teammates grows. In this case, it may be difficult for more diverse teams to remain intact even if skill diversity leads to higher team productivity.

The economic theories summarized in this section suggest that diversity in skill level and ability enhances team productivity through task coordination and knowledge sharing within the team. In contrast, demographic diversity along such dimensions as age and ethnicity may harm productivity by making communication too costly and making peer pressure less effective.

Demographic diversity also could lead to increased levels of team-member turnover, while the implication for the impact of skill diversity on turnover is ambiguous.

PRODUCTION AT KORET

The empirical context for analyzing the predictions of the theoretical models described above is the Koret Corporation garment manufacturing facility in Napa, California, first studied in HNO (2003). The facility produces ''women's lowers'' including pants, skirts, and shorts.[14] These garments are mid-priced clothes purchased and distributed by department stores. Prior to 1994, the factory utilized a Taylorist progressive bundling system (PBS) (e.g., Dunlop and Weil, 1996) for production in which seamstresses were paid an individual piece rate based on performance of the assigned task relative to an administratively set standard.[15] Workers typically specialized in one task, such as sewing pockets.

In response to retailers' demands for just-in-time delivery, Koret slowly introduced modular work teams of generally 5–8 workers in the factory starting in late 1994. While teams and PBS employees worked side-by-side on the factory floor during this period, using the same capital and materials, the teams were empowered to make a variety of production decisions, such as the assignment of tasks and the sequence of operations. They were paid a group piece rate based on the number of garments the team produced, with the receipts divided equally among members.[16] Participation in teams was initially voluntary, with nine teams formed by the end of 1995.[17] Workers were not able to freely pick up their own team members (i.e., volunteers were assigned into teams by management), but they were presumably able to coordinate and sort into the same team by volunteering at the same time. Furthermore, they had the option of returning to PBS production or switching teams if this was acceptable to the new team. As noted in HNO (2003), the success of team production was such that in mid-1996, the manager decided to convert the entire plant to modular production system. There was no noticeable change in the attrition rate at the time of this entire shift to the module production.

The data for our analysis consists of weekly information on productivity and team membership for all individuals and teams employed at Koret from January 1, 1995, until December 31, 1997. Productivity is measured as efficiency relative to the standard, with values greater than 100 indicating performance above the standard level. The ethnicity and birth date of each worker also was obtained, although further data on education, training, and so forth was not available to us. A critical feature of the data is that because most employees worked under both PBS and modular production systems, we are able to construct measures of individual productivity for each worker at the plant prior to their team membership. This allows us to separate the impacts of skill diversity and demographic diversity on team performance. For workers who had never worked under the PBS, the skill diversity measure for the groups they belong to are calculated without their individual productivity. Those workers are also excluded from the individual level turnover analysis.

Table 1 presents summary statistics for the team-week data, indicating substantial variation in weekly team productivity across teams and over time. These productivity differentials translate into substantial variation in worker pay. Comparing team productivity with the average productivity in individual production of the team members, both the 50th and 75th percentiles suggest that teams increased productivity, while the difference at the 25th percentile suggests that for at least some teams and/or weeks, teams were less productive. The much greater variance of team productivity compared to that of the team members under individual production implies that match quality and expectations of team members (which were likely to be affected by how and when teams were formed) might have generated substantial differences in the effectiveness of teamwork. Finally, there appears to be substantial variation in the ethnic composition of teams as measured by the faction of Hispanics among team members.

Table 1. Distributions of Team Productivity, Pay, and Composition.

Variable	Quantile		
	.25	.50	.75
Productivity	80.30	98.24	114.02
Weekly earnings per member	$219.04	$294.65	$361.52
Average team skill[a]	83.61	91.31	102.49
Average team age	33.4	35.7	39.2
Fraction Hispanic	0.33	0.50	0.80
Number of team-week observations		2012	

[a]Average team skill measured as average productivity of team members under individual production.

Measuring Diversity in Teams

The knowledge sharing model in the first section suggests that the most able worker on a team at Koret will have a strong influence on team productivity due to the help she can provide to less able members and through knowledge transfer. Similarly, the least able member may gain substantial help from other members and learn the most from teamwork. Consequently, following HNO (2003), we measure skill diversity within the team by the ratio of the maximum to the minimum average individual productivity levels of the team members.[18] This ratio also is a reasonable measure of diversity in estimating the impact on turnover because the most able and the least able workers should be the most likely to leave the team.

For our first measure of demographic diversity, we use the standard deviation of the natural logarithm of the ages of team members. The standard deviation of ln(age) implies that percentage rather than absolute differences in the age of team members affects communication among individuals. For example, one might argue that communication may be more difficult between a 20- and 30-year-old than between a 40- and 50-year-old.[19]

Our second measure of demographic diversity considers the ethnic/racial composition of the team. Nine ethnic/racial groups are represented at Koret.[20] Fifty-four percent of the workers are Hispanic, followed by 12% who are Vietnamese; most are recent immigrants. While we experimented with a variety of diversity measures, such as a Herfindahl index for the "shares" of each ethnic group on the team at a point in time, we decided to measure ethnic/racial diversity by an indicator variable for whether all team members belong to the same ethnic group because a key link between demographic diversity and communication costs is a common language. All of the ethnically homogeneous teams at Koret consist of Hispanics who speak Spanish. Our ethnic diversity measure *All Hispanic* takes the value one for 213 out of 2012 team $\times$ week observations. Seven out of the 23 teams in our study have some weeks in which the team consists of entirely Hispanic workers. Only one team is composed of entirely Hispanic workers over almost all of the sample period. Consequently, there is some within-team variation in the ethnic composition of teams that is sufficient to produce statistically significant result.

A particular advantage of the Koret data is that we are able to observe individual productivity prior to team membership for many workers, and so we are able to distinguish between diversity in skill and diversity in demographic characteristics. It is still possible that different demographic groups possess different skills and knowledge sets that are valuable and complementary with each other in the teamwork setting, and thus the impact of demographic diversity is compound (e.g., captures the effect of skill diversity in some dimensions). But we do believe that such possibilities are very limited in this Koret case, because (1) the production process is very simple and does not require much cognitive skills, (2) most operations are routine and coordination is necessary only when tasks have to be allocated or re-allocated among team members, and (3) there is little interactions with management or other groups;

SORTING AND INITIAL TEAM FORMATION

In this section, we examine how workers initially sorted into teams. Our model suggests that workers may choose teams that are heterogeneous in terms of ability to take advantage of learning opportunities as long as the skill difference is not so excessive as to cause the break-up of the team. They also may choose teams that are demographically homogeneous to reduce communication and discrimination costs and make peer pressure more effective. Columns 1–6 of Table 2 summarize the skill and demographic characteristics of each team at the date of formation, including average worker productivity for individuals prior to joining the team and the amount of skill and demographic diversity. To examine sorting into teams, the table also compares actual team characteristics with the characteristics of simulated teams formed randomly from workers in the firm. We construct these simulated teams by drawing 1,000 teams of a particular size (e.g., seven members) from the employees of the firm including those already in teams as of a particular date.[21] The characteristics of these simulated teams are recorded, and the mean, 5th, and 95th percentile summary statistics are reported in the rows labeled ***Random*** in Table 2. We conduct these simulations at dates corresponding to the dates of large waves of team formation at the firm. Comparison of the actual and simulated team characteristics provides insight into the role that sorting plays in initial team formation.

The table displays a number of notable findings. Columns 1 and 2 show that teams formed in 1994 and 1995 tend to be comprised of more able workers and have greater diversity in skill, perhaps in an attempt to capture the benefits of mutual learning. Teams 2, 3, and 7, which consist of relatively less able workers, have the greatest diversity in individual productivity. However, it is still the case that the level of diversity falls within the 90%

Table 2. Initial Team Characteristics and Average Weekly Team Productivity, Actual and Randomly Formed Teams.

Team	Date Team Formed	Mean Individual Productivity[a]	Max/Min Individual Productivity	Mean ln(Age)	S.D. of ln(Age)	Fraction Hispanic	Fraction with Prior Team Experience	Team Productivity (Weeks 21+)[b]
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Teams formed on Jan. 7, 1995, or earlier								
1	3/12/94	97.8	1.57	3.30	0.22	0.71	0	114.3
2	1/7/95	82.9	4.36	3.46	0.09	0.71	0	122.6
Random	1/7/95	91.4	2.54	3.56	0.28	0.50	0.05	
		[74.9, 111.5]	[1.52, 5.00]	[3.38, 3.74]	[0.17, 0.39]	[0.14, 0.86]	[0, 0.14]	
Teams formed on Jan. 28, 1995								
3	1/28/95	79.4	2.45	3.30	0.22	1.00	0	97.6
4	1/28/95	94.0	2.09	3.31	0.26	0.36	0	106.0
5	1/28/95	117.8	1.50	3.57	0.38	0.21	0	118.9
6	1/28/95	89.4	2.40	3.40	0.18	0.42	0.17	88.3
Random	1/28/95	89.6	2.24	3.55	0.28	0.50	0.08	
		[70.1, 111.2]	[1.28, 4.65]	[3.33, 3.77]	[0.13, 0.42]	[0.20,0.80]	[0, 0.40]	
Teams formed in April–October 1995								
7	4/29/95	89.6	2.95	3.43	0.23	0.83	0.17	107.8
8	10/7/95	122.6	1.79	3.56	0.23	0.00	0.57	115.6
9	10/28/95	127.4	2.15	3.70	0.27	0.29	0.17	131.3
Random	4/29/95	92.3	2.20	3.54	0.28	0.50	0.27	
		[75.6, 112.3]	[1.37, 3.69]	[3.34, 3.74]	[0.15, 0.41]	[0.17, 0.83]	[0, 0.67]	
Teams formed in 1996								
10	4/13/96	85.6	1.46	3.64	0.32	0.44	0	83.6
11	3/30/96	100.4	1.78	3.65	0.27	0.21	0.29	111.8
12	4/13/96	87.3	2.10	3.45	0.25	0.48	0.14	109.3

Table 2. (*Continued*)

Team	Date Team Formed	Mean Individual Productivity[a]	Max/Min Individual Productivity	Mean ln(Age)	S.D. of ln(Age)	Fraction Hispanic	Fraction with Prior Team Experience	Team Productivity (Weeks 21 +)[b]
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
13	4/13/96	94.6	3.18	3.68	0.16	0.17	0.14	106.1
14	4/13/96	85.6	1.64	3.77	0.19	0.37	0.14	91.2
15	5/18/96	78.3	1.25	3.61	0.33	0.67	0.13	76.8
16	6/22/96	81.1	3.17	3.42	0.43	0.67	0.17	82.6
17	7/20/96	81.7	1.41	3.63	0.26	0.80	0.83	122.9
18	4/13/96	92.6	1.62	3.61	0.28	0.00	0.33	95.5
19	4/13/96	86.1	1.95	3.60	0.38	0.60	0	79.7
20	8/10/96	127.5	2.10	3.65	0.39	0.33	1.00	114.4
21	12/7/96	–[c]	–	3.39	0.18	0.50	0	139.1
Random	4/13/96	97.4	2.38	3.53	0.26	0.50	0.28	
		[80.4, 118.2]	[1.48, 3.99]	[3.36, 3.69]	[0.15, 0.37]	[0.14, 0.86]	[0, 0.57]	
Teams formed in 1997								
22	1/18/97	94.0	1.50	3.35	0.35	0.57	0.57	80.0
23	2/1/97	89.2	1.30	3.55	0.30	0.83	0.29	70.9
24	3/15/97	92.1	1.85	3.44	0.20	0.80	0.67	61.2
25	9/6/97	76.9	6.45	3.66	0.12	0.57	0.43	–
Random	1/18/97	96.4	2.18	3.56	0.28	0.48	0.86	
		[79.4, 111.9]	[1.37, 3.63]	[3.37, 3.74]	[0.16, 0.40]	[0.14, 0.83]	[0.57, 1.00]	

Note: Entries in the rows labeled ***Random*** represent the summary statistics of 1,000 simulated teams formed randomly from the workers at the firm as of the given date. Entries in brackets represent 5th and 95th percentiles.

[a]Entries in column 1 are calculated by average the individual person-week productivity values of workers who subsequently join the particular team.

[b]Team averages in column 7 calculated after excluding the first 20 weeks the team is in operation.

[c]Team 21 consisted of almost all new hires and so pre-team productivity is not available.

confidence interval associated with random formation of the teams. Teams formed in 1996 and 1997, when team participation was less voluntary, have lower average skill and are less diverse in terms of ability. In addition, these teams tend to be of lower ability and have less skill diversity than would be expected if the teams were randomly selected from workers at the firm. This may reflect the inability of these teams to poach relatively-high-ability workers from teams formed earlier. Indeed, the entries in column 6 for the 1996 and 1997 teams indicate that fewer team members have previous team experience than would be expected if teams were randomly selected.

Later teams tend to be more diverse in terms of age, as evidenced by column 4. Again, the earlier teams may have been more able to reduce communication costs due to their ability to ‘‘hand-pick’’ their teammates. In addition, column 5 provides relatively little evidence of substantial worker segregation across teams. Only team 3 was initially formed with all Hispanic workers, and 9 teams out of 25 are comprised of two-thirds or more Hispanics. With the exception of team 8, no team has over half of its members belonging to one of the other ethnic/racial groups.[22] The ethnic diversity of teams at Koret appears to be roughly in line with what would be expected if teams formed randomly.

Finally, comparison of columns 1 and 7 indicates productivity increases in 14 of the 23 teams for which we have valid pre- and post-team data. Teams formed in 1995 are the most likely to show a productivity increase, while teams formed in August 1996 and later (when team participation was less voluntary) experience declines. As discussed in HNO (2003), it may be the case that workers with greater collaborative skills joined the early teams.[23] This interpretation is supported by a more recent study by Woolley, Chabris, Pentland, Hashmi, and Malone (2010), who find that a group's performance on a variety of tasks can be explained by ‘‘collective intelligence,’’ which is not necessarily strongly correlated with the average or maximum intelligence of group members but substantially correlated with the average social sensitivity of the members.[24]

While turnover will be discussed more thoroughly below, the initial team rosters described in Table 2 are remarkably durable. Fig. 1 shows the fraction of founding team members remaining on the team at the end of the sample period in December 1997. Five of the seven members of team 1, founded in 1994, are still on the team as of December 1997, as are five of the original seven members of team 8. On the other hand, a few teams experienced substantial turnover, such as teams 6 and 19, which have no original members by the end of the period. In some cases, workers from these teams left the firm altogether, while others joined another team at

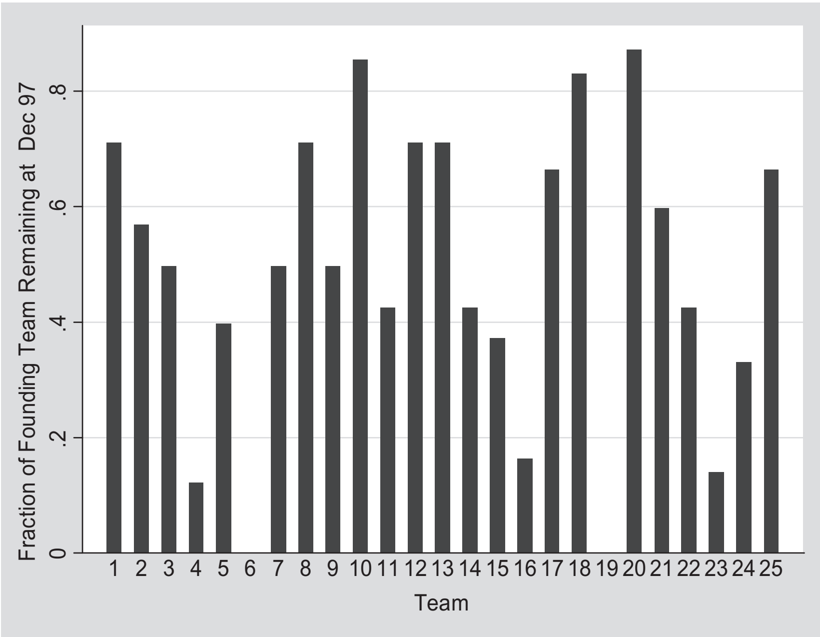

Fig. 1. Fraction of Founding Team Members Remaining as of December 31, 1997.

Koret, sometimes as a founding member. It should be noted that multiple teammates rarely left a team at the same time, and changes in team rosters generally occurred gradually as one team member left during a given period.

THE IMPACT OF DIVERSITY ON PRODUCTIVITY

In this section, we investigate the impacts of skill heterogeneity and demographic diversity on productivity in teams at Koret. The theory outlined above suggests that teams with more diverse skills will be more productive, all else equal, because highly productive workers can substantially increase the production of the least able workers on the team by helping, teaching, or coordinating activities. Conversely, our model suggests that if demographic diversity increases communication costs, more heterogeneous teams in terms of age and/or ethnicity should be less productive.

Let Y_{jt} be the natural logarithm of the productivity of team j in week t at Koret. A team's weekly productivity is modeled as

$$Y_{jt} = X_{1jt}\alpha + X_{2jt}\beta + X_{3jt}\delta + \varepsilon_{jt} \tag{6}$$

where X_{1jt} consists of measures of the productivity of team j's members at date t, such as the average individual productivity level and the spread in individual abilities. The vector X_{2jt} consists of measures of the demographic characteristics of team j's members at date t, including the average ln(age), the standard deviation of ln(age), and an indicator of whether the team consists of all Hispanic workers at date t. X_{3jt} includes additional variables thought to affect team productivity, such as a polynomial in the number of weeks the current members of the team have worked together (*TENURE*), an indicator of whether the team includes a new hire with no previous Koret experience (*NEWHIRE*), and the size of the team. To account for possible selection effects, a variable indicating that the team was formed in April 1996 or later (*LATER TEAM*) also is included. We include variables accounting for seasonality in Koret's production that might affect employment.[25] We do not have complete data on team 1, and team 21 initially consisted entirely of outsiders for whom we have no pre-team productivity data. Consequently, these two teams are not included in the regression analysis described below.

The OLS estimates of Eq. (6) are shown in the first column of Table 3. Not surprisingly, teams with more able members, on average, are more productive. More striking is the finding that holding ability constant, teams with more diverse skills also tend to be more productive. The estimated positive relationship between the spread in skill and productivity is consistent with our theoretical predictions.[26]

The coefficient estimate in the fourth row of column 1 indicates that teams with more diversity in age are less productive, although the coefficient estimate is not strongly significant. This finding is consistent with Leonard and Levine (2006a), who find that retail stores with greater age diversity among its employees tend to be less profitable. However, Leonard and Levine are not able to determine the extent to which employees in their study work together in teams. A variety of studies in the organizational behavior literature find similar negative impacts of age diversity on alternative measures of team performance (see Reskin & Charles, 1999). For example, Zenger and Lawrence (1989) find that age homogeneity enhances technical communication. However, these papers typically do not distinguish between the roles of diversity in skill versus heterogeneity in the demographic characteristics of team members.

Table 3. Effect of Team Composition on Team Productivity.

Dependent Variable is ln(Productivity$_{jt}$) for Team in Each Week				
Variable	Specification			
	OLS	Fixed Effects	Fixed Effects	Fixed Effects
	(1)	(2)	(3)	(4)
Average productivity	0.004	0.006	0.009	0.008
	(0.002)	(0.001)	(0.003)	(0.002)
Ratio of max/min productivity	0.057	0.045	0.055	0.026
	(0.020)	(0.015)	(0.023)	(0.021)
Mean ln(Age)	0.166	0.022	−0.680	0.551
	(0.172)	(0.157)	(0.292)	(0.210)
S.D. ln(Age)	−0.330	−0.158	−0.096	0.346
	(0.214)	(0.208)	(0.532)	(0.237)
All Hispanic	0.125	0.078	0.054	0.065
	(0.045)	(0.063)	(0.101)	(0.085)
TENURE	0.051	0.042	0.047	0.024
	(0.008)	(0.007)	(0.010)	(0.011)
$TENURE^2/10$	−0.026	−0.021	−0.026	−0.009
	(0.006)	(0.004)	(0.006)	(0.008)
$TENURE^3/1,000$	0.049	0.039	0.051	0.015
	(0.012)	(0.010)	(0.014)	(0.023)
$TENURE^4/10,000$	−0.003	−0.002	−0.003	−0.001
	(0.001)	(0.001)	(0.001)	(0.002)
NEWHIRE	−0.019	0.072	0.125	−0.030
	(0.043)	(0.037)	(0.059)	(0.052)
LATER TEAM	−0.105	–	–	–
	(0.048)			
Sample	All teams	All teams	Teams formed prior to April 1996	Teams formed after March 1996
No. of observations	2012	2012	1125	887

Note: Standard errors in parentheses. Standard errors adjusted to account for clustering by team. Robust standard errors for OLS and Fixed Effect regressions. Each regression also includes a constant, the number of team members, dummies for each month, and cyclical variables measuring women's retail garment sales.

Estimates of our second measure of demographic diversity, the team's ethnic composition, provide support for the view that demographically homogeneous teams have lower communication costs that lead to higher productivity. Column 1 shows that teams comprised of one ethnic group

(Hispanics) are 12.5% more productive than ethnically diverse teams at Koret.

One concern about the estimates described above is that there may be unobserved team characteristics correlated with the diversity measures that also affect productivity. We have two plausible interpretations that are in line with such unobservable factors. First, the literature on organizations highlights the idea that teams (and organizations) are often "imprinted" at their founding. Such imprinting can be thought of as the establishment of a set of norms that are durable even in the face of turnover. For example, Simon (1991) describes how turnover in organizations will not necessarily lead to changes in culture because new members are indoctrinated with established social norms. In addition, Stinchcombe (1965) argues that initial environmental conditions can create organizational imprints that endure. Consequently, the characteristics of the founding members (e.g., demographic diversity) or the circumstances under which the team was formed, such as the support and commitment from management, may have long-lasting impacts on productivity.

Second, the demographic characteristics of a team may be endogenous to the level of collaborative skills of team founders. Suppose the workers' utility is concave in income and they enjoy non-pecuniary utility of participating in a demographically homogeneous team (i.e., "taste for discrimination"). Then, expecting to earn a relatively higher team pay, workers with higher collaborative skills will be more likely to afford forming a demographically homogenous team by inviting friends rather than most productive workers they know. If early team founders have more collaborative skills than late team founders as discussed earlier in this chapter and in HNO (2003), the former may have afforded to choose teammates who have similar demographic characteristics (e.g., in the same age and ethnic group). In other words, high productivity may be the cause not the result of high demographic diversity. Table 2 seems to be consistent at least in terms of age with this hypothesis.

To account for the potential confounding role of time-invariant team-level unobserved factors discussed above, we estimate fixed effect models of Eq. (6). As noted in the third section, in most cases a change in the team roster involves the replacement of one worker, rather than wholesale changes in the team. Therefore, the impact of diversity on productivity is identified by marginal changes in the composition of a team (i.e., the replacement of a single team member by another worker). Note that the fixed effect estimates may understate the effects of various diversity measures if founding members have the greatest impact on productivity by setting routines and communication patterns that persist in the teams (i.e., the first interpretation we discussed above).

After including team fixed effects in the regression, column 2 of Table 3 shows that increasing the average skill level of the team increases productivity, as was the case in the OLS regression. Moreover, increasing the skill diversity of the team, holding the average constant, continues to positively affect team productivity. On the other hand, the coefficient estimate of the ethnic diversity measure shown in column 2 does not appear to be robust to the inclusion of team fixed effects. The productivity of teams composed solely of one ethnic group falls to 7.8% and is not significantly different from that of more ethnically diverse teams. This finding may imply that established team norms impacting productivity are not necessarily altered by marginal changes in the team's demographic composition or unobserved collaborative skills of team founders may have influenced the demographic composition of the teams.

Alternative Specifications

The model of task coordination and knowledge sharing in the first section suggested that the impact of skill diversity on team performance might be further enhanced in some situations if communication costs are lower. To examine this possibility, we first re-estimated Eq. (6) including interactions between the skill and demographic diversity measures. We found no evidence that the productivity of teams with high skill diversity was enhanced if they were more demographically homogeneous.[27]

To further investigate the link between skill diversity and communication costs, we note in Table 3 that teams formed after April 1996 (*LATER TEAM*), when team participation was less voluntary, were significantly less productive than those formed in 1994 and 1995. HNO (2003) argue that the teams formed when participation was voluntary were likely to have greater collaborative skills that enhanced their productivity. Indeed, Table 2 suggests that these teams attracted workers with higher individual productivity, which is likely to be correlated with collaborative skills. Consequently, one might expect the impact of skill diversity to be greater for teams formed prior to April 1996 if collaborative skills enhance knowledge sharing. Columns 3 and 4 of Table 3 present fixed effects estimates of Eq. (6) for the two groups of teams. Skill diversity has a positive and significant impact on productivity for teams formed prior to April 1996. The coefficient estimate declines and is no longer statistically significant for the teams formed when participation was virtually mandatory. If early teams did indeed have greater collaborative skills, this finding suggests that the learning effect induced by skill diversity is enhanced by this factor.[28]

Tenure Profiles

The estimated relationship between the length of time team members have worked together and productivity implied by the coefficient estimates in Table 3 provides insight into the implicit costs of worker turnover. As in the wage-tenure profile literature, a positive relationship between *TENURE* and productivity may be generated by at least two factors. First, team-specific capital, which enhances mutual learning and collaboration (and hence productivity), will be accumulated as the team works together. Second, particularly well-matched teams will have higher levels of collaborative capital from the team's inception and are more likely to stay together, generating a positive relationship between tenure and productivity. Using the coefficient estimates from column 1 of Table 3, Fig. 2 plots the

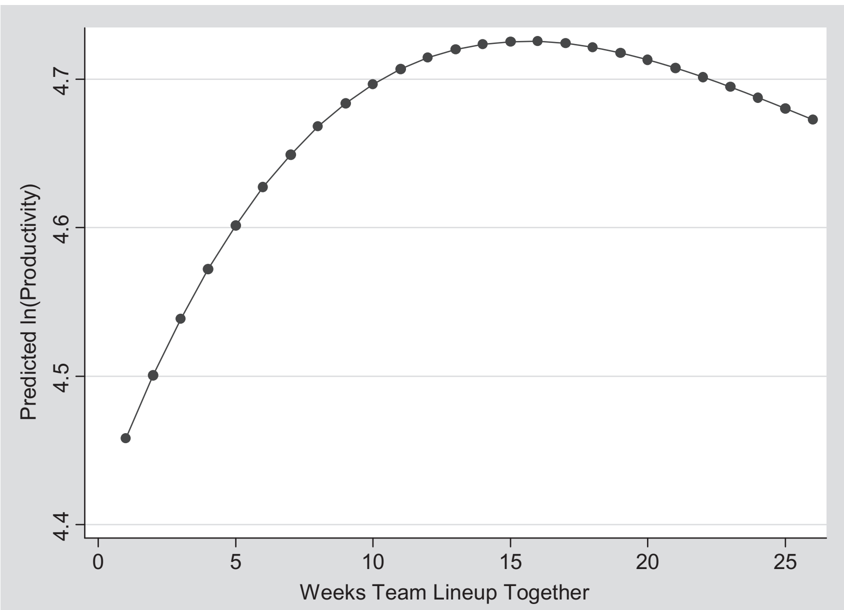

Fig. 2. Relationship Between Team Tenure and Productivity.

tenure-productivity profile for a team with average characteristics. The concave tenure profile shown in the figure suggests that turnover may indeed be costly for Koret. A team that has worked together for six months (26 weeks) is estimated to be approximately 25% more productive than a team that has just formed. If members of diverse teams are more prone to leave, the implicit cost of diversity may be quite high in terms of lost productivity.

Overall, the results from Table 3 suggest that skill diversity raises team productivity, which is consistent with the observation that there is substantial learning and coordination at Koret. This finding is robust across specifications. There is mixed evidence regarding the role that demographic diversity plays, since the results are sensitive to assumptions regarding unobserved factors that may be correlated with team formation. Marginal changes in demographic diversity do not significantly affect team performance.

DIVERSITY AND TURNOVER

We now examine the relationship between individual and team characteristics and turnover. As described in the first section, heterogeneity in worker abilities and demographic characteristics affect the utility associated with participation on a particular team in two ways. First, skills and other characteristics may impact team productivity, and hence pay. Second, these factors may directly influence utility through peer pressure effects or preferences for working with particular groups of co-workers. To investigate these issues we proceed in two steps. First, we estimate hazard models at the team level to determine the relationship between team characteristics and turnover. We then estimate models at the worker level to investigate the impact of an individual's characteristics relative to those of her teammates on the decisions to leave the firm or switch teams

Team-Level Estimates

We use the 245 distinct lineups at Koret between 1995 and 1997 to investigate the impact of team characteristics on the conditional probability of a change in team composition. The empirical hazard rate shown in Fig. 3 indicates that the conditional probability of team dissolution declines sharply with team experience. Together with the rising productivity-tenure

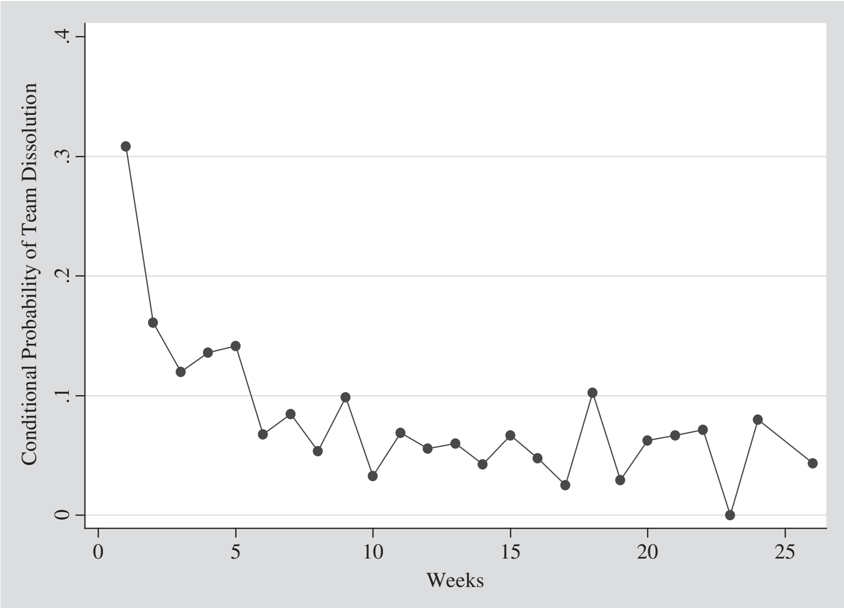

Fig. 3. Empirical Hazard of Team Dissolution.

profiles discussed above, the empirical hazard rate is consistent with the notion that poorly matched teams break up quickly, while those with higher levels of collaborative capital tend to remain together. The next step is to determine the extent to which the skill and demographic characteristics of the team affect the quality of the match.

To assess the impact of observed team characteristics, we estimate a Cox proportional hazards model for the length of time the team remains together:

$$\lambda(TENURE_{js}|X_{1jst_0}, X_{2jst_0}, X_{3jst_0}) = \exp(X_{1jst_0}\theta_1 + X_{2jst_0}\theta_2 + X_{3jst}\theta_3) \times \lambda_0(TENURE_{js}) \tag{7}$$

where s indexes the lineup spell of team j for the team lineup that was formed at date t_0, and X_1, X_2, and X_3 are as defined in Eq. (6), with the obvious exception that X_3 now excludes *TENURE*. Note that X_3 includes cyclical factors that are allowed to vary over the course of the spell.

The hazard estimates shown in the first column of Table 4 provide mild support for the view that demographic diversity may be associated with

Table 4. Cox Proportional Hazard Estimates for Probability of Team Turnover.

Team-Level Models		
Variable	(1)	(2)
Average productivity	−0.002	0.002
	(0.005)	(0.005)
Ratio of max/min productivity	0.019	0.049
	(0.074)	(0.074)
Mean ln(Age)	−0.229	0.060
	(0.627)	(0.625)
S.D. ln(Age)	0.400	0.458
	(0.778)	(0.787)
All Hispanic	−0.541	−0.389
	(0.311)	(0.316)
LATER TEAM	0.323	0.181
	(0.206)	(0.213)
SIZE	−0.102	−0.097
	(0.066)	(0.066)
Team productivity	–	−0.009
		(0.003)
Log likelihood	−1018.7	−970.4

Note: Based on $N = 242$ team-lineup spells. Standard errors in parentheses. Each model includes month dummies and cyclical variables measuring women's retail garment sales.

higher turnover in teams. While skill and age diversity do not have a strong impact on the hazard rate, the results in column 1 show that teams composed entirely of Hispanics are less likely to break up, although this effect is only significant at the 10% level. Given our finding in Table 3 that all Hispanic teams were more productive, this may simply reflect the fact that these teams are paid more. We assess this explanation in column 2, where we include lagged team productivity in the hazard model to distinguish between the effects of diversity on productivity and pay versus preferences for teammates.[29] Holding team productivity constant, the demographic variables are likely to reflect preferences toward working with similar individuals. The estimates show that more productive (and hence more highly paid) teams are significantly more likely to remain intact. Moreover, the impact of ethnic diversity on team turnover becomes insignificant once team productivity is added to the specification, suggesting that worker' tastes for discrimination do not play a central role in explaining the length of time a team remains together.

Worker-Level Estimates

The results in Table 4 show that skill diversity does not significantly impact team dissolution. However, theoretical predictions for the impact of skill diversity on turnover are mixed due to countervailing effects. Highly skilled workers may be more likely to be poached away, but their position as the "chief problem solver" on the team may be a source of non-pecuniary benefit. On the other hand, low-skilled workers may face overwhelming peer pressure to quit, but they gain substantial monetary compensation by remaining on a high quality team. We now examine the extent to which the worker's relative position on the team, in terms of both skill and demographics, affects turnover as suggested by the theoretical models in the first section.

To analyze the impact of diversity on individual turnover at Koret, we construct individual team-participation spell data for the 189 workers who spent at least one week on a team during 1995–1997. Some workers either switched teams or had more than one stint on a given team, yielding a total of 328 spells of team participation. We examine how the conditional probabilities of leaving the team vary over the course of the worker's team spell, and distinguish between two possible reasons for exit: leaving to join another team (denoted by reason $r = o$) and exit from the firm or a return to individual production ($r = e$). Very few workers leaving a team return to individual production, so virtually all $r = e$ exits represent an employee leaving the firm completely.

Fig. 4 plots the empirical transition intensities for workers leaving their teams to join another team or to leave Koret, over the first six months on the team. Like the team-level hazard, the conditional probability of leaving a team for any reason initially declines after the first few weeks on the team. One interpretation of the negative duration dependence observed in Fig. 4 is that learning about teammates' attributes is important when forming a team. Poor matches of the individual worker with the team end relatively quickly. Of course, it may also be the case that a worker may temporarily participate on one team while waiting for a space on another team to open. However, this argument cannot explain why the conditional probability of leaving the firm, as opposed to switching teams, declines roughly monotonically from week one.

To incorporate the impact of covariates on the conditional probability of leaving a team at Koret, we estimate an independent competing risks model. The transition intensity for worker i leaving team j after τ weeks at calendar date t for reason r, $\lambda_r(\tau)$ follows a proportional hazards specification:

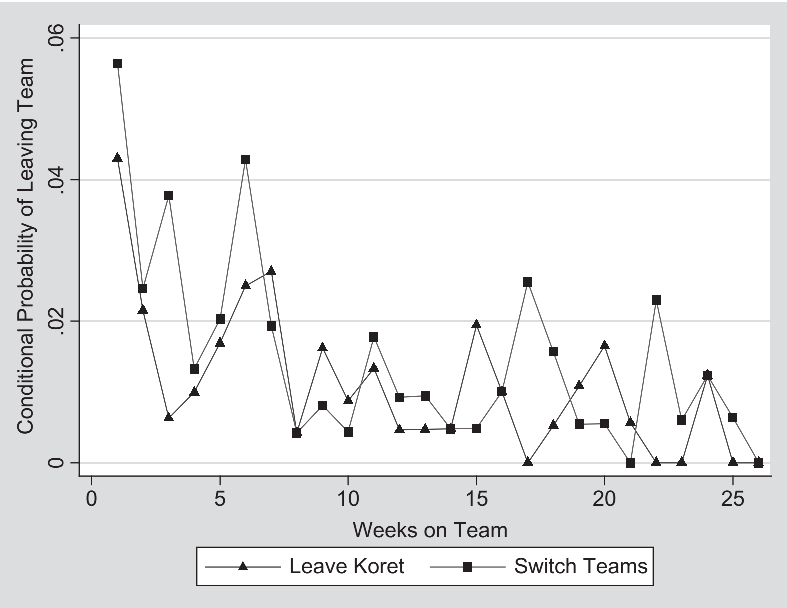

Fig. 4. Worker-Level Empirical Transition Intensities.

$$\lambda_r(\tau|Z_{1i0}, Z_{2ijt}, X_{3jt}, W_t) = \exp(Z_{1i0}\gamma_{1r} + Z_{2ijt}\gamma_{2r} + X_{3jt}\gamma_{3r} + W_t\omega_r) \\ \lambda_{0r}(\tau), \quad r = e, o \tag{8}$$

The vector Z_{1i0} consists of worker i's demographic and productive characteristics at the time she joins the team, including age, ethnicity, individual productivity level, and whether she was one of the team founders or a new hire. Z_{2ijt} measures the worker's relative position on the team in terms of skill and demographic characteristics at date t.[30] Although it is difficult to measure peer pressure within the team, it may be reasonable to assume that peer pressure is related to the difference between the worker's individual productivity and the productivity of the team.[31] For skill and age, we follow studies such as Leonard and Levine (2006b) and measure relative position as the absolute value of the distance between the worker's characteristics and the average of those for the team. Workers may prefer team members from the same ethnic group or may feel less peer pressure if they are not a member of the dominant ethnic group on the team (Towry, 2003). We include an indicator if the worker is the only member of his ethnic group on the team (*TOKEN*), as well as an indicator of whether at least two-third of the team's other members belong to one ethnic group (*ISOLATED*) that is different from worker *i*'s. The vector X_{3jt} includes team-level variables that potentially affect turnover, including *SIZE*, *LATER TEAM*, and, in some specifications, lagged team productivity. Finally, over the course of the three-year period under study, there were an increasing number of teams available to which a Koret worker could switch. To measure the impact of the changing team opportunity set for the individual, the vector W_t consists of dummy variables indicating whether week τ of the spell occurred during particular periods defined by the number of teams in operation at the plant, as well as the seasonality measures included in the earlier regressions.[32]

The estimates in the first row of Panel A of Table 5 indicate that more skilled workers are less likely to switch teams (column 3). However, the coefficient becomes insignificant once lagged team productivity is included in the specification (column 4), suggesting that more skilled workers tend to have higher ability teammates. Holding the ability of teammates constant, the second row of Panel A suggests that team "stars" tend to get poached by other teams, although the coefficient estimate declines in magnitude and significance when team productivity is accounted for. Other teams may recognize the knowledge-sharing benefits of these workers for productivity, as shown in Table 3, as well as the positive spillover in payoff having a very productive teammate. Note that if workers placed a high value on being the "star" of the team (negative peer pressure), we would expect this coefficient to be negative rather than positive. There is little evidence that team "sloths" (the low-skilled workers on the team) are forced to quit due to peer pressure. For these individuals, peer pressure seems not so intense as to offset the substantial monetary benefit from team membership.

With regard to demographic characteristics, the third and fourth rows of Panel B show that Hispanic workers appear to be more attached to Koret than White or Asian workers although there is no significant ethnic difference in the propensity to switch teams. The estimates in column 3 provide mild evidence that being the only member of one's ethnic group on the team (*TOKEN*) encourages switching, but again, this appears to reflect productivity effects. Surprisingly, the "token effect" reverses when the remainder of the team is ethnically homogeneous. Even after controlling for team productivity, such "isolated" workers are less likely to switch teams. As noted in the organizational behavior literature described above, isolated workers may experience less peer pressure, or it may be less effective, because they do not share the overlapping social ties of the dominant ethnic

Table 5. Cox Transition Intensity Estimates for Leaving Team.

Worker-Level Models				
Variables	Exit event			
	leaves firm		Switches teams	
	(1)	(2)	(3)	(4)
Panel A: Skill characteristics				
Individual productivity	−0.008	−0.004	−0.014	−0.004
	(0.011)	(0.012)	(0.007)	(0.008)
|Individual – avg prod.|	0.007	0.004	0.026	0.018
Above avg. prod.	(0.018)	(0.018)	(0.011)	(0.012)
|Individual – avg prod.|	−0.006	−0.003	−0.006	0.007
Below avg. prod.	(0.014)	(0.014)	(0.008)	(0.009)
Team founder	−0.600	−0.229	0.109	0.078
	(0.414)	(0.440)	(0.211)	(0.229)
New hire	0.271	0.331	−0.588	−0.819
	(1.310)	(1.309)	(0.622)	(0.229)
Panel B: Demographic characteristics				
ln (Age)	−1.223	−1.223	0.118	0.135
	(0.716)	(0.721)	(0.360)	(0.367)
|Individual – mean ln (Age)|	−0.659	−0.601	−0.216	−0.120
	(1.411)	(1.407)	(0.655)	(0.675)
White	2.097	1.827	−0.751	−0.537
	(1.205)	(1.203)	(0.803)	(0.815)
Asian	1.898	1.812	−0.221	−0.146
	(0.465)	(0.468)	(0.274)	(0.284)
TOKEN	0.028	0.122	0.485	0.240
	(0.445)	(0.454)	(0.294)	(0.314)
ISOLATED	−0.787	−0.830	−1.133	−0.889
	(0.639)	(0.644)	(0.502)	(0.513)
Panel C: Team characteristics				
LATER TEAM	−1.104	−1.097	0.537	0.375
	(0.542)	(0.561)	(0.286)	(0.295)
SIZE	−0.346	−0.374	0.145	0.127
	(0.133)	(0.134)	(0.090)	(0.099)
Team productivity[a]	–	−0.009	–	−0.012
		(0.009)		(0.005)
Log likelihood	−174.5	−169.5	−549.5	−503.7

Note: Based on $N = 328$ worker-team spells. Standard errors in parentheses. Each model includes indicators month dummies, and cyclical variables measuring women's retail garment sales.

[a]Team productivity measured by average team productivity in previous four weeks.

group and are more difficult to sanction. Alternatively, individuals may choose to join and remain on otherwise homogeneous teams because they have a preference for diversity.

Workers in the teams formed in April 1996 or later are less likely to leave the firm but more likely to switch teams, although the latter effect is insignificant and disappears once the team's productivity is accounted for. The result is consistent with our earlier explanation, also stated in HNO (2003), that workers with greater collaborative skills joined the early teams. Workers with greater collaborative skills may have higher outside options; thus, they are more likely to leave; at the same time, they are more likely to enjoy higher team productivity; thus, they stay with the initial team.

Overall, the results from this section suggest that there is relatively low cost to the firm in terms of turnover of diverse work teams. The primary driver of both team dissolution and individual turnover is team productivity and hence pay. Particularly well-matched teams with high levels of collaborative skill are likely to be more productive and remain intact. The impacts of skill and demographic diversity operate primarily through their impact on productivity. To the extent that peer pressure or prejudice exists in teams at Koret, the negative effect on utility appears to be offset by the positive impact on team productivity.

DISCUSSION AND CONCLUSION

Teamwork is a central feature of modern organizations. As such, the relationship between the composition and management of teams and their productivity is of general interest to managers and economists alike. An emerging economic literature emphasizes the role of collaborative skills or "connective capital" in the firm's production function (e.g., Ichniowski, Shaw, & Gant, 2003). This chapter assesses the "business case for diversity" by examining the effects of various dimensions of team member diversity on productivity in production teams by first introducing models linking various types of diversity to team-member turnover and team productivity in a production setting. The models show that diversity in ability enhances team productivity if there is ample opportunity for mutual learning and task coordination within the team. In contrast, demographic diversity harms productivity by making learning and peer pressure less effective and by increasing team-member turnover. Consequently, the set of complementary models explains the impact of both skill and demographic diversity in the same framework, which we then use to interpret our data.

Based on the implications of our theoretical models, we use a novel data set from a garment factory that introduced teams over a three-year period, which allows us to empirically analyze the impact of team diversity on productivity and worker turnover. Our analysis differs from prior work on teams due to the panel nature of our data and because we observe individual productivity prior to joining a team, which allows us to econometrically distinguish between the impacts of diversity in worker abilities and demographic diversity. The results indicate that teams with more heterogeneous worker abilities are more productive. Ethnic diversity has a negative effect: holding the distribution of team ability constant, teams composed only of one ethnicity (Hispanic workers in our case) are more productive. However, our fixed effect estimates suggest that marginal changes in the team's ethnic composition (i.e., replacing a single worker on the team) do not significantly impact team productivity, while the effect of skill diversity persists. Founding members may set patterns of communication that persist even when the team's membership changes.

Turnover costs associated with diversity appear to be modest, since the most productive teams are more likely to remain intact. The most able workers are more likely to be poached by other teams; controlling for team pay, ethnic diversity does not appear to directly impact the probability of switching teams or leaving Koret. To the extent that peer pressure or prejudice exists in teams at Koret, the negative effect on utility appears to be offset by the positive impact on team productivity. In addition, relatively few ethnically homogeneous teams are founded initially, indicating that workers have little preference for segregation.

Given the relatively simple production technology at the garment plant we study, one may not expect communication costs in teams, as represented by demographic diversity, to have a large impact on productivity. It would be useful to determine whether the same is true at firms where teams engage in more complex problem-solving tasks. However, even in simple production environments, there appears to be a business case for skill diversity, since productivity is higher in these teams.

NOTES

1. Quote from Lew Platt, former CEO of Hewlett-Packard, to the Diversity Research Network, Stanford Business School, March 18, 1998, reported in Kochan et al. (2003). See Leonard and Levine (2006a) for discussion of the benefits of diversity.

2. Note that some observed benefits of ethnic diversity at the country or community level (Alesina & La Ferrara, 2005) do not necessarily imply gains from ethnic diversity at the level of work organization.

3. Lazear's conclusions resonate with a long history of research in organizational behavior. For recent examples, see Jehn, Northcraft, and Neale (1999), Reagans and Zuckerman (2001), and Pelled, Eisenhardt, and Xin (1999). Other research in economics and organizational behavior also emphasizes the importance of communication costs. For instance, Arrow (1974) was one of the first to focus on the effects of within-team communication costs on performance. More recent research suggests that demographic differences are likely to increase communication costs. For example, McCain, O'Reilly, and Pfeffer (1983), O'Reilly, Caldwell, and Barnett (1989), and Zenger and Lawrence (1989) find that age differences within teams reduce communication. Lang (1986) shows that language differences and racial and gender diversity increase communication costs. In contrast, Barrington and Troske (2001) do not find a significant relationship between demographic diversity and productivity at the establishment level, although they do not explicitly control for skill diversity in their analysis.

4. Encinosa, Gaynor, and Rebitzer (2007) examine the relationship between informal interactions within the group, such as monitoring and mutual help, and the compensation system chosen by medical group practices. In an experimental setting, Falk and Ichino (2006) find that low-ability workers are more responsive to peer pressure than high ability workers. Mas and Moretti (2006) find that the introduction of high-productivity supermarket workers on a shift increases the productivity of their co-workers. This spillover effect increases with worker interaction.

5. They find that individuals internalize more of the externality that their effort generates under a relative incentive scheme when their co-workers are close friends.

6. Using match-level data from the German soccer league, Nüesch (2009) shows that the correlations between age diversity and the outcome of the game disappear once a measure of relative playing ability is accounted for.

7. Lazear (1999) and Cummings (2004) imply that some skills and knowledge sets are specific to certain demographic, cultural, or functional groups, and there are gains from forming groups with diverse characteristics.

8. See Leonard (1984), Heckman and Payner (1989), Conrad (1995), Holzer and Neumark (2000), and Leonard et al. (2010), for example.

9. Our skill measure may not fully capture the skills useful in the team production setting (communication skills, leadership, etc.). If other skills and knowledge that affect team productivity are correlated with demographic characteristics, we are still unable to distinguish the effects of skill and demographic diversity. Hansen (1997) and Hansen, Owan, and Pan (2011) also discuss the importance of distinguishing demographic and skill diversity in evaluating the impact of diversity.

10. HNO (2003) also presents an intra-team bargaining explanation in which workers negotiate over common work pace that is perceived as the team norm. In their argument, skill diversity is likely to raise productivity because the highest-ability worker may credibly threaten to opt out unless the other workers agree to a higher team norm. As long as the proposed team norm is not excessive for the majority of the workers, they will accept it to retain the highest-ability worker.

11. Although the firm may gain by letting the most productive workers to choose their tasks, other workers are worse off by such practice and therefore oppose it. Also, in the long run, piece rates for those tasks may be adjusted if they are consistently chosen by most productive workers, and therefore, able workers may oppose such practices as well.

12. The implication that skill diversity has greater impact as communication costs fall is also consistent with our finding from a numerical example shown in Appendix B.

13. What is surprising about their result is that this peer effect arises even though workers are paid based on their individual performance and therefore there are no externalities due to the pay scheme.

14. Garment production at the plant is segmented into three stages. First, cloth is cut into pieces that conform to garment patterns. Finished garments may contain anywhere between 2 and 10 individual pieces including pockets, fronts, backs, waistbands, belt-loops, etc. Second, garments are constructed by sewing together pieces. Third, garments are finished by pressing, packaging, and placing them into a finished goods inventory where they await delivery to a storage warehouse or to customers. Our study focuses on the sewing operation.

15. "Standard" is an expected sewing time in minutes set for each operation and typically ranges between 0.5 and 2.0 minutes per operation. Management assigns the standard to each new operation, in consultation with the union, such that the amount of effort required to sew a standard minute is equivalent across tasks, thus making the comparison of productivity across tasks and garments feasible.

16. Piece rates per garment for modules are equal to the sum of standard minutes for all operations required to make the entire garment with one exception: each worker under the PBS must unbundle and bundle the stack of garments when it arrives and leaves the workstation whereas bundling and unbundling are not needed between operations – only when raw material bundles first arrive and finished goods bundles finally leave the work area – under the module production system. Thus, the standard for an entire garment is five percentage points lower for modules. However, worker productivity of PBS and module production is measured in comparison to standard minutes, not garments, which means that worker productivity measures for each are directly comparable.

17. The members of the first team (formed in late 1994) were handpicked by the general manager. This team is not included in our analysis.

18. HNO (2003) estimated models using the standard deviation of average individual productivity levels of team members as well as the ratio of the maximum to the minimum average individual productivity levels; the results were virtually identical between the two measures. We prefer the max–min ratio mainly because, as we state in the main text, the theory suggests that the most productive worker has a much greater effect on team productivity than any other members; the empirical analysis in HNO (2003) supports this view.

19. Leonard and Levine (2006a) argue that the standard deviation of ln(age) provides a better measure of social distance than the standard deviation of age.

20. These ethnic/racial groups include Hispanics, whites, blacks, Filipinos, Chinese, Japanese, Vietnamese, Indians, and Koreans.

21. Because workers could switch teams without penalty and such changes were not rare, including the workers already in teams in our simulations is appropriate.

22. The non-Hispanic members of teams where Hispanic employees are a minority generally come from two or more of the ethnic groups working at Koret.

23. Table 2 shows that team 21, which consisted primarily of new hires with no Koret experience, was highly productive. We suspect that this team was "hand-picked" by management, since it consisted of young workers in their early twenties from a range of ethnic backgrounds. Because no pre-team productivity data is available, team 21 is excluded from the team regressions reported in Tables 3 and 4.

24. They also find that the collective intelligence is increasing in the proportion of women. This further reinforces the view that it is difficult to distinguish the effects of skill and demographic characteristics.

25. Output at Koret exhibited substantial seasonal variation. To account for this factor, we obtained monthly data on U.S. women's retail apparel sales over the period from the Bureau of Economic Analysis. We include period t retail sales as well as sales up to six months in the future as regressors in the X_{3jt} vector, since such future sales may translate into current period demand for Koret output. Because the retail sales variable is seasonally adjusted, month dummies are also included to account for cyclical factors.

26. In an earlier version of this chapter, we presented the results of median regression to eliminate the effect of potential outliers. The estimated effect of skill diversity was robust to this alternative estimation method.

27. The p-values from the test of the null hypothesis that the coefficients on the interactions between skill diversity and demographic diversity were jointly zero were 0.885 and 0.749 in the OLS and fixed effects regressions, respectively.

28. Table 3 also suggests that there is no non-linearity in the relationship between the skill diversity and the productivity as is found in Papps, Bryson, and Gomez (2011). If excessive skill diversity is detrimental to the productivity, marginal change in the skill diversity should have had lower correlation with the productivity for teams formed before April 1996 because those teams have higher average skill diversity. Theoretically, excessive disparity in skills could cause coordination failures if work pace are too different or impede knowledge sharing if slow workers lack the capacity to learn techniques from far more productive workers. Skills differences in the Koret factory are not so great as is shown by our later analysis that teams with greater skill diversity are no more likely to break up than other teams. It may be so because the management screen job candidates.

29. The measure of lagged team productivity used in the duration model is the average productivity over the previous four weeks. The results are not sensitive to changes in the lag length.

30. There may be some concern about the potential endogeneity of the Z_{2jjt} variables as they vary over the course of the spell. We re-estimated the models shown in Table 5 measuring the covariates included in Z_{2jjt} at the time the worker joined the team. This approach yields very similar results to those reported in Table 5.

31. Workers whose individual productivity was low may find it difficult to raise effort enough to meet the team norm, and so may face additional peer pressure that reduces the utility associated with remaining on the team.

32. From Table 2, we define a set of dummy variables indicating whether period ϑ of the spell fell during: (a) weeks 32–67, when teams 1–9 were operating; (b) weeks 68–101, when teams 1–20 were operating; (c) weeks 102–135, when teams 1–23 were operating; (d) weeks 136–155, when all teams were operating at Koret.

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APPENDIX A: FORMAL PROPOSITIONS AND PROOFS

Consider an increase in the variance of $\{\lambda_1,\ldots,\lambda_N\}$ such that the skill gap between two arbitrary workers expands while preserving the mean of $\{\lambda_1,\ldots,\lambda_N\}$ (*i.e.*, λ_i increases and λ_j decreases by the same amount when $\lambda_i > \lambda_j$ but other λ_k's do not change). How does such a change affect team productivity? While skill diversity tends to increase Y in (4) in general, an increase in $\lambda_i' - \lambda_i > 0$ does not have a monotone effect on Y. In order to demonstrate that skill diversity typically has positive impact on team productivity through task coordination and knowledge sharing, we prove the claim for two special cases and also present numerical examples.

Proposition 1. When $N = 2$, a mean-preserving increase in $\lambda_2 - \lambda_1$ raises Y.

Proof. $Y = 2 + \lambda_1 d_1 + \lambda_2 d_2 + |(1-h)(\lambda_2 - \lambda_1)d_1 - h(2 + \lambda_1 d_1 + \lambda_2 d_2)|_+$. When there is no knowledge sharing, namely $(1-h)(\lambda_2 - \lambda_1) d_1 - h(2 + \lambda_1 d_1 + \lambda_2 d_2) \leq 0$, we only evaluate the effect of task coordination and the result is trivial. So, assume $(1-h)(\lambda_2 - \lambda_1)d_1 - h(2 + \lambda_1 d_1 + \lambda_2 d_2) > 0$ and suppose λ_2 increases and λ_1 decreases by the same amount $\Delta\lambda$ (i.e., mean-preserving increase). Then, $\Delta Y / \Delta\lambda = (1-h)(d_2 - d_1) + 2(1-h)d_1 > 0$. This concludes the proof.

Proposition 2. Suppose $d_1 = d_2 = \equiv d$ and $h_{ij} = h$, a mean-preserving increase in $\lambda_{i'} - \lambda_i$ weakly raises Y for any $i' > i$.

Proof. $Y = N + \sum_{i=1}^{N} \lambda_i d + \sum_{i=1}^{N} \max_{j>i} |(1-h)(\lambda_j - \lambda_i)d - h(2 + \lambda_i d + \lambda_j d)|_+$. Note that, when $(1-h)(\lambda_j - \lambda_i)d - h(2 + \lambda_i d + \lambda_j d)$ is positive, it is increasing in λ_j and decreasing in λ_i. Hence, there exists $\hat{i}$ such that $(1-h)(\lambda_N - \lambda_i)d - h(2 + \lambda_i d + \lambda_N d) \geq 0$ for all $i \leq \hat{i}$, and $Y = N + \sum_{i=1}^{N} \lambda_i d + \sum_{i=1}^{\hat{i}} \{(1-h)(\lambda_N - \lambda_i)d - h(2 + \lambda_i d + \lambda_j d)\}$.

A mean-preserving increase in $\lambda_{i'} - \lambda_i$ does not change Y when either $\hat{i} \geq i' > i$ *or* $N > i' > i > \hat{i}$. When $N > i' > \hat{i} \geq i$ or $N = i'$, a mean-preserving increase in $\lambda_{i'} - \lambda_i$ clearly raises the third term. This concludes the proof.

APPENDIX B: NUMERICAL EXAMPLE

To illustrate the empirical implications of our results and see interaction between skill diversity and demographic diversity, we construct the following numerical example.

Suppose that $N = 5$ and $\lambda_i \in \{0.5-2\eta, 0.5-\eta, 0.5, 0.5+\eta, 0.5+2\eta\}$, where skill diversity is parameterized by η. Three levels of skill diversity will be compared: high ($\eta = 0.15$), medium ($\eta = 0.1$), and low ($\eta = 0.05$). Task heterogeneity is assumed by $d_i \in \{0.3, 0.4, 0.5, 0.6, 0.7\}$. We also examine the impact of increasing levels of communication costs: Team productivities for each parameterization are compared in Fig. A1. The percentage changes are calculated compared with the case when there is no task coordination and knowledge sharing (i.e., the value expressed in (2)). Team productivity improves as the skill diversity measured by η increases and communication costs decrease. The numerical simulation shown in the figure also indicates that the benefit of skill diversity is greater as communication costs decline, because low communication costs encourage more knowledge sharing, whose return is an increasing function of skill diversity.

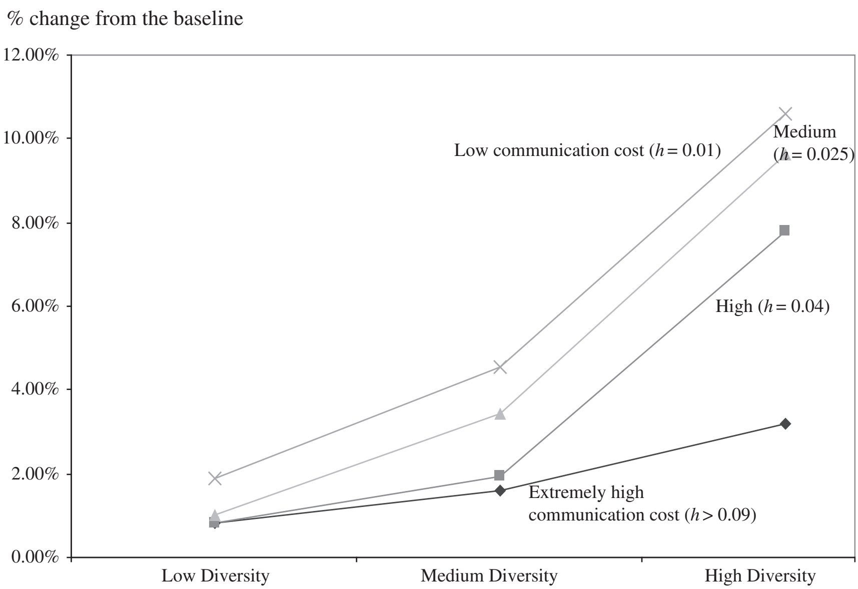

Fig. A1. Gains from Knowledge Sharing and Task Coordination. *Notes*: The baseline is the productivity expressed in Equation (2), which assumes that tasks are assigned randomly and workers do not share knowledge.