Diversity and Productivity in Production Teams

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ABSTRACT

The popular press often touts workforce demographic (e.g., ethnicity and age) diversity as profit enhancing. Diversity 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 in teams thereby retarding problem-solving and diminishing productivity. Unfortunately, the effect of team diversity on productivity has not been studied formally and there is little empirical evidence concerning the impact of diversity on productivity. Diversity in ability enhances the team productivity if there is significant mutual learning and collaboration within the team, while demographic diversity is likely to 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. Our results indicate that teams with more heterogeneous worker abilities are more productive. Holding the distribution of team ability constant, teams with greater diversity in age are less productive, and those composed only of one ethnicity (Hispanic workers in our case) are more productive, but the findings for team demographics are not robust to alternative model specifications. Finally, workers on all Hispanic teams are less likely to leave the team, even after accounting for team productivity, indicating some preference for segregation among these workers.

Keywords: Teams, diversity, productivity, turnover, learning, sorting, compensating differentials, collaborative skills.

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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, few formal arguments and empirical research on productivity have explored the business case for diversity.

In this paper, we investigate the latter claim that "diverse teams produce better results" in a production setting with a relatively simple technology. Lazear (1998a, 1998b) 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

[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. (2002). See Leonard and Levine (2002) for some discussions on the benefits of diversity.

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, that reduce communication costs or what he calls "costs of cross-cultural dealing."[2]

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.[3] Their theory implies that partnerships among homogeneous workers are advantageous because mutual monitoring and social sanctions are effective at punishing deviators. A number of authors including Reagans and Zuckerman (2001), Spagnolo (1999), and Towry (2003) emphasize the importance of social ties or social capital in

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[2] Lazear's conclusions resonate with a long history of research in organizational behavior. For recent examples see Jehn et al. (1999), Reagans and Zuckerman (2001), and Pelled et al. (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 et al. (1983), O'Reilly et al. (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. Yet, overall, research suggests that more demographically diverse teams may be less productive, holding skill diversity constant, because high communication costs hinder coordination and learning.

[3] Encinosa, Gaynor, and Rebitzer (2003) examine the relationship between informal interactions within the group, such as monitoring and mutual help, and the compensation system chosen by medical group practices.

encouraging cooperation in 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.

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 may also reduce worker utility. If workers are prejudiced, then 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 as well as explain 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 because of self-reporting biases. Consequently, it is difficult to empirically separate the role of skill diversity from communication costs induced by demographic diversity in teams. Moreover, team membership over time often is not available. Researchers then are forced to examine the role of demographic heterogeneity at the firm or plant level. However, diversity at the plant level may mask substantial segregation among teams within a particular location, which will bias productivity and turnover estimates. 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 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. Because we observe productivity in individual production for almost all workers that eventually join a team, we are able to construct measures of both skill level and 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. Similarly, because we focus on teams operating side-by-side within in the same factory, our results will not be 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 with greater diversity in age are less productive, and those composed only of one ethnicity (Hispanic workers in our case) are more productive, but these findings are not robust to alternative specifications of the regression model. Finally, teams that are more productive (and hence receive higher pay) are more likely to remain intact, although workers on all Hispanic teams are less likely to leave even after accounting for lagged team productivity, indicating some preference for segregation among these workers.

1. Theoretical Background

We develop a model which captures two different consequences of diversity that seem to be relevant to team production in the context of the garment factory we analyze. First, diversity in skills and ability may enhance the productivity of a team because more skilled workers help and teach the less skilled, and teammates gain more from task coordination.[4] Second, demographic diversity potentially inhibits within-team communication and thus reduces both the effectiveness of collaboration and peer pressure, as well as the non-pecuniary benefit of joining the team. Our model builds on the work of Kandel and Lazear (1992) and Kandori (2003), and

[4] HNO (2003) also presents an intrateam bargaining explanation in which workers negotiate over common work pace that is perceived as team norm. In their argument, skill diversity is likely to raise productivity because the highest-ability worker may credibly threat to opt out unless the other workers agree with 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.

includes the benefit of collaboration between workers with difference skill levels and psychological payoff from team participation.

The Model

HNO (2003) argues that two kinds of learning are promoted by teams: collective and mutual learning, which can be viewed as knowledge creation and knowledge transfer. 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 skillful workers to the less skilled. Workers learn how to execute tasks better and more quickly from each other.

Consider a team with N workers where workers are indexed by $i \in \{1, 2\ldots N\}$. Assume that the team operates over an unspecified number of discrete time periods. In each period, each worker makes a decision about how much total effort, e_i, to exert by incurring personal cost of $c_i(e_i)$. e_i is measured in efficiency units and differences in $c_i(e_i)$ represent skill heterogeneity. To simplify our notation, we assume the quadratic cost function $c_i(e_i) = \frac{e_i^2}{2c_i}$ and use c_i as a parameter of a worker's technical skill. Let $\mathbf{e} = \{e_1, e_2, \ldots, e_N\}$.

In teamwork, the benefit of a worker's effort depends on the skill distribution within the team. Because more productive workers can teach the less productive how to do tasks faster and better, the effect of work effort by high-skill workers is greater as the differences in skill levels are larger. Task coordination also is more effective when workers are heterogeneous in skills because team can improve productivity by assigning tasks to those who have relative advantage in doing so. For example, team can assign difficult tasks to more productive workers and easy tasks to less productive ones and adjust the assignment continuously in light of new information. We assume that the total team output is given by:

$$Q = \sum_{i=1}^{N} f_i(c_1, ..., c_N)e_i \qquad (1.1)$$

where $f_i \geq 1$ for any *i* and f_i is nondecreasing in c_i and nonincreasing in $c_{-i} = (c_1, ..., c_{i-1}, c_{i+1}, \ldots c_N)$. The last assumption captures the notion that the technical skill is substitutable, namely that one's skill is more valuable when the others do not have the skill. Let $\mathbf{f} = (f_1, \cdots f_N)$. $\mathbf{f}$ is symmetric in the sense that $f_i(c_1, \cdots, c_N) = f_{\pi(i)}(c_{\pi^{-1}(1)}, \cdots, c_{\pi^{-1}(N)})$ for any permutation π.

For comparison, we assume that the firm can also design the work organization so that the production function is separable in c_i, and workers only perform assigned tasks with no possibility of cooperation and coordination. Under individual production, the total output of worker *i* is given by $\underline{q}_i = e_i$. Consequently, $(f_i(c_1, ..., c_N) - 1)e_i$ is the additional output created by the worker's collaborative effort that could make team production more productive than individual production.

A worker's utility depends on her team pay *W*, disutility of total effort $c_i(e_i) = \dfrac{e_i^2}{2c_i}$, disutility from peer pressure, and psychological payoffs from socialization and the less repetitive nature of work. A worker's pay is an equal portion of the team pay, which depends on the piece rate, *w*, and the team output *Q* expressed in (1,1). Hence, $W = \dfrac{w}{N}Q$. We assume that $\mathbf{e}$ is observable to all team members and the mean of $\mathbf{e}$ in the prior period, *m*, becomes the standard or *team norm* in the current period. Peer pressure arises when workers perform below the team norm and is proportional to the deviation. Utility from peer pressure thus takes the form $-k[m - e_i]$. Other psychological payoffs from joining a team are represented by b_i. Hence, team-member i's utility is:

$$\begin{aligned} u_i(W, e_i, m) &= W - c_i(e_i) - k[m - e_i]_+ + b_i \\ &= \frac{w}{N}\sum_{i=1}^{N} f_i(c_1, \ldots, c_N)e_i - \frac{e_i^2}{2c_i} - k[m - e_i]_+ + b_i \end{aligned} \tag{1.2}$$

Note that all parameters and variables are specific to the team that worker i belongs to and variables could change over time. We omit subscripts for team identity and time for notational simplicity.

A couple of comments about our specification are in order. First, we can easily show that when $c_1 < c_2 < \cdots < c_N$, $f_1(c_1, \ldots, c_N) \leq f_2(c_1, \ldots, c_N) \leq \cdots \leq f_N(c_1, \ldots, c_N)$ from the assumptions on **f**. Because a more productive worker faces a higher return from her effort, lower marginal cost of effort and the same peer pressure, she exerts no less effort than less productive workers. Second, a change in non-skill-related heterogeneity is expected to reduce f_i and k holding technical and collaborative skill distributions constant because differences in personal background or language hinder communication needed to coordinate activities and development of trust among team members, which are backbones of collaboration. If workers have "tastes for discrimination" as Becker (1957) argues, demographic differences in a team could also affect non-monetary payoff from working in team, b_i. Specifically, benefits may be reduced if the worker is not part of the majority group on the team, due to tastes for discrimination or isolation.

Equilibrium

We look for the steady-state level of effort and team norm. We call $\mathbf{e}^* = (e_1^*, \ldots, e_N^*)$ and m^* the *steady-state equilibrium* when

$$u_i(\mathbf{e}^*, m^*) \geq u_i(\mathbf{e}^*_{-i}, e_i, m^*) \text{ for all } i \text{ and } e_i, \qquad m^* = mean(\mathbf{e}^*). \tag{1.3}$$

Workers are boundedly rational in the sense that they do not choose e_i's strategically taking into account their impact on m and the evolution of other members' decisions. Therefore, this equilibrium is not a Nash equilibrium. Note that key interactions among e_i's take place through m. An increase in worker j's effort e_j should raise m and gives an additional incentive to worker i who would try to avoid peer pressure. We first identify $\mathbf{e}^*$ that satisfies $u_i(\mathbf{e}^*, m^*) \geq u_i(\mathbf{e}^*_{-i}, e_i, m^*)$ for all i and e_i given exogenously fixed m^*. Assume $c_1 < c_2 < ... < c_N$ without loss of generality.

Lemma 1

$$e_i^* = c_i(\frac{wf_i}{N} + k) \text{ when } m^* > c_i(\frac{wf_i}{N} + k),$$
$$e_i^* = m^* \text{ when } \frac{wc_i f_i}{N} \leq m^* \leq c_i(\frac{wf_i}{N} + k), \text{ and}$$
$$e_i^* = \frac{wc_i f_i}{N} \text{ when } m^* < \frac{wc_i f_i}{N}.$$

Proof: The result is straightforward from (1.2).

Figures 1 and 2 illustrate the optimal choices of effort given the team norm for a team of six members. In Figure 1, workers are relatively homogeneous (*i.e.* $\frac{wc_N f_N}{N} < c_1(\frac{wf_1}{N} + k)$). In this case, all team members follow the team norm and choose the same effort level. Furthermore, there will be a continuous set of equilibria: any number between $\frac{wc_N f_N}{N}$ and $c_1(\frac{wf_N}{N} + k)$ could be the equilibrium team norm (see the shadowed area in Figure 1). Figure 2 illustrates a more heterogeneous team in terms of skill level. Workers 1 and 2 are the least productive workers on the team and they receive peer pressure to work harder. Workers 3 and 4 are mediocre workers who are productive enough to achieve the team norm but can do so only under the threat of peer pressure. Worker 5 and worker 6 are the most productive workers whose efforts are so effective that the piece rate alone gives them sufficient incentives to choose effort levels that are higher than the team norm.

Now we derive the steady-state team norm. Lemma 1 gives the best response function from the team norm in period *t*, m_t to the workers' effort choices in the same period $\mathbf{e}_\mathbf{t}^*$. Since the team norm in the next period is obtained by m_{t+1} = mean($\mathbf{e}_\mathbf{t}^*$), this creates the mapping from the team norm in the current period to that in the next period. Let *M(m)* be this mapping. The steady-state equilibrium can be found by solving *M(m)* = *m*.

Proposition 1 There always exists a steady-state equilibrium $(m^*, \mathbf{e}^*)$. The equilibrium is unique if $\frac{wc_N f_N}{N} \geq c_1(\frac{wf_1}{N}+k)$.

Proof: see Appendix.

Impact of Demographic Diversity

We now analyze how heterogeneity affects the equilibrium. From Lemma 1, the team norm in the steady-state equilibrium is

$$M(m) = \frac{1}{N}\sum_{i=1}^{N}\min(c_i(\frac{w}{N}f_i + k),\ \max(\frac{wc_i f_i}{N}, m)) \tag{1.4}$$

and the team output is

$$Q^* = \sum_{i=1}^{N} f_i \min(c_i(\frac{w}{N}f_i + k),\ \max(\frac{wc_i f_i}{N}, m^*)) \tag{1.5}$$

As discussed above, non-skill-related diversity is likely to reduce f_i and *k* by making communication and coordination more costly and peer pressure through social networks less likely. Because $M(m)$ is a nondecreasing function of f_i's and *k*, greater demographic diversity should lower the function $M(m)$ thus reducing the team norm m^*. Therefore, demographic diversity measures should be correlated with lower team output.

Impact of Skill Diversity

The impact of a change in skill heterogeneity is challenging to analyze because we must assess the change in the profile $\mathbf{c} = \{c_1, c_2, \ldots, c_N\}$. For any skill diversity measure, team output does not increase or decrease monotonically with the measure because the impact is typically sensitive to how many team members are working harder or slower than the team norm. In the extreme case, if workers are very homogeneous and there are an infinite number of equilibria, an increase in skill diversity simply reduces the range of feasible team norms offering no clear implication about whether the team output will increase or decrease.[5] However, experiments with simple functions indicate that whether the average impact of skill diversity is positive or negative depends on the magnitude of the gain created by collaborative effort. Intuitively, if $\sum_{i=1}^{N} f_i(c_1, \ldots c_N)$ is increasing in skill diversity at a significant rate holding the mean of $\mathbf{c}$ constant, skill diversity tends to improve the team productivity. To illustrate this point, consider a two-player team and a simple technology $f_i(c_1, c_2) = \alpha \,|\, c_i - c_j \,|_+ + 1$ where $|x|_+$ denotes $\max\{x, 0\}$. α indicates the effectiveness of collaboration. If $c_2 > c_1$, $f_1(c_1, c_2) = 1$ and $f_2(c_1, c_2) = \alpha(c_2 - c_1) + 1$. We study the mean-preserving change of (c_1, c_2) by taking $c_1 = \bar{c} - \gamma$

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[5] In Figure 3, as c_1 decreases and c_6 increases, the upper limit for the equilibrium team norm $c_1(\frac{wf_1}{N} + k)$ falls and the lower limit $\frac{wc_6 f_6}{N}$ rises.

and $c_2 = \bar{c} + \gamma$. This change does not affect the average productivity of the same workers when they work individually because it is expressed by $\frac{q_1 + q_2}{2} = w\frac{c_1 + c_2}{2} = w\bar{c}$. How will the increase in γ affect the team output?

From Lemma 1, there exists a number $\hat{\gamma}(\alpha)$ such that for any $\gamma < \hat{\gamma}(\alpha)$, m^* cannot be determined uniquely and $e_1 = e_2 = m^*$.[6] $\hat{\gamma}(\alpha)$ is decreasing in α. The feasible range for team norms m^* is $[\frac{w(\bar{c}+\gamma)}{2}(2\alpha\gamma+1),\ (\bar{c}-\gamma)(\frac{w}{2}+k)]$ and

$$Q \in [w(\bar{c}+\gamma)(2\alpha\gamma+1)(\alpha\gamma+1),\ (\bar{c}-\gamma)(w+2k)(\alpha\gamma+1)] \tag{1.6}$$

Because the upper limit may or may not increase with γ, it is not clear how skill diversity influences team output. When $\gamma \geq \hat{\gamma}(\alpha)$, m^* is determined uniquely, and $e_1 = (\bar{c}-\gamma)(\frac{w}{2}+k)$ and $e_2 = \frac{w(\bar{c}+\gamma)}{2}(2\alpha\gamma+1)$. Then, $Q = (\bar{c}-\gamma)(\frac{w}{2}+k) + \frac{w(\bar{c}+\gamma)}{2}(2\alpha\gamma+1)^2$. Now,

$$\frac{dQ}{d\gamma} = -(\frac{w}{2}+k) + \frac{w}{2}(2\alpha\gamma+1)^2 + 2\alpha w(\bar{c}+\gamma)(2\alpha\gamma+1) \tag{1.7}$$

This derivative implies that the impact of skill heterogeneity is indeterminate. There exists a number $\tilde{\gamma}(\alpha,\bar{c})$ such that the team output Q is decreasing in γ for $\gamma < \tilde{\gamma}(\alpha,\bar{c})$ but increasing for in γ for $\gamma > \tilde{\gamma}(\alpha,\bar{c})$. $\tilde{\gamma}(\alpha,\bar{c})$ is decreasing in both α and $\bar{c}$. There are two countervailing effects: team norm erosion and the enhanced gains from learning and task coordination. If α is small and thus $\tilde{\gamma}(\alpha,\bar{c})$ is large, the former dominates the latter for most teams because the replacement of a low-productivity worker with even less productive one has

[6] $\hat{\gamma}(\alpha)$ is determined by solving $\frac{w(\bar{c}+\gamma)}{2}(2\alpha\gamma+1) = (\bar{c}-\gamma)(\frac{w}{2}+k)$.

more impact on team norm than the replacement of a high-productivity worker with even more productive one due to the asymmetry of incentive intensity (*i.e.* $\frac{wf_1}{2}+k$ vs. $\frac{wf_2}{2}$).

As α increases, both $\hat{\gamma}(\alpha)$ and $\tilde{\gamma}(\alpha,\overline{c})$ decline making the range of γ greater for which *Q* is increasing in γ. Consequently, when there is substantial learning and task coordination within team, team output is more likely to be positively correlated with skill diversity. Know-how shared by a highly skilled worker has more value when there are many workers who possess little skill, and task allocation and its continuous adjustment in accordance with the skill distribution generates more value when skill diversity is great.

Impact on Turnover

To derive the implications for turnover, let $\underline{u}_i$ be the outside option value available for worker *i* after she quits her team. Worker *i* should leave her team when $u_i - \underline{u}_i < 0$. It is natural to assume that $\underline{u}_i$ is non-decreasing in c_i. Now compare $u_i - \underline{u}_i$ among team members *i = 1, …, N*. Remember that all team members receive the same team pay *W*. Then,

$$
\begin{aligned}
u_i - \underline{u}_i &= W - \frac{c_i}{2}(\frac{wf_i(\mathbf{c})}{N}+k)^2 - k[m^* - c_i(\frac{wf_i(\mathbf{c})}{N}+k)] + b_i - \underline{u}_i(c_i) \text{ when } m^* > c_i(\frac{wf_i(\mathbf{c})}{N}+k) \\
u_i - \underline{u}_i &= W - \frac{c_i}{2}m^{*2} + b_i - \underline{u}_i(c_i) \text{ when } \frac{wc_i f_i(\mathbf{c})}{N} \le m^* \le c_i(\frac{wf_i(\mathbf{c})}{N}+k) \\
u_i - \underline{u}_i &= W - \frac{c_i}{2}(\frac{wf_i(\mathbf{c})}{N})^2 + b_i - \underline{u}_i(c_i) \text{ when } m^* < \frac{wc_i f_i(\mathbf{c})}{N}
\end{aligned}
\tag{1.8}
$$

Remember that when $c_1 < c_2 < \cdots < c_N$, $f_1(c_1,...,c_N) \le f_2(c_1,...,c_N) \le \cdots \le f_N(c_1,...,c_N)$. If b_i and η_i are constant over *i*, it is easily checked that the second and the third functions in (1.8) are decreasing in *i* while the first may be increasing in *i* if *k* is large. Thus, the most productive worker or the least productive should want to leave the team first. The most productive worker may want to leave the team because she expects to earn more in other teams or under individual production. The least productive worker may want to leave the team because peer pressure is unbearably high for her. Therefore, unless collaborative skills and psychological payoffs are highly correlated with technical skills, we should tend to see these workers leaving teams.

Team participation decisions will be less clear than separation decisions because workers with different skill levels may form different expectations about their income in teams. If their expectations are similar and peer pressure is not expected to be large, less productive workers should join teams first because they could free-ride on the work of more productive workers. Surprisingly, the results in HNO (2003) indicate that more productive workers tend to join teams first. This result may imply that k (the impact of peer pressure on utility) was expected to be high, which discouraged less able workers from joining teams, or that psychological utility of joining a team b_i was systematically higher for more productive workers.

In this paper, we ask the question of who is more likely to switch teams when team characteristics affect f_i and k, and workers receive different psychological utility of joining a team b_i. Because demographic diversity may reduce the equilibrium payoff by lowering team productivity through lower f_i and k and reducing non-pecuniary benefits of working on a team, greater demographic differences might also raise team-member turnover. Normally, team diversity in skills and ability should raise the turnover, because the most productive worker is more likely to receive higher pay by switching teams. How skill diversity affects the turnover of least productive workers is less clear. The least productive worker is likely to experience disutility from strong peer pressure, but she also benefits from the productivity gain derived from skill diversity. When team diversity in skills and ability are beneficial to team productivity, the above impact of skill diversity on the turnover of most productive worker will be partly offset by the additional gain from collaboration.

To summarize, our model argues that diversity in skill level and ability enhances team productivity if there are significant mutual learning and task coordination within the team. In contrast, demographic diversity along such dimensions as age and ethnicity is likely to harm productivity by making learning and peer pressure less effective. Demographic diversity also should lead to increased levels of team-member turnover.

2. Production at Koret

Our empirical context for analyzing the model predictions is weekly productivity reports from a Koret Corporation garment manufacturing facility in Napa, California. The facility produces "women's lowers" including pants, skirts, shorts, etc.[7] These garments are mid-priced clothes purchased and distributed by department stores. Along with many other firms in the garment industry, a major reason for the introduction of team production over the 1995 – 1997 period at Koret was the demand by retailers that apparel companies make just-in-time deliveries. As noted by Berg et al. (1996), such demands required more flexible production systems, and pushed manufacturers like Koret to replace traditional individual production methods with more flexible teams. Because module production was expected to decrease costs through reductions in inventory, manufacturing space, supervisory and service functions, quality inspections, and rework, many apparel manufactures were willing to adopt a team system even if worker productivity fell.

[7] 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.

Progressive bundling system production

Historically, the plant used a Taylorist progressive bundling system (PBS) (e.g., Dunlop and Weil (1996)) for production. In PBS production, sewing operations are broken down by management into a number of distinct and separate operations depending on the complexity of the garment. Management, in consultation with the union, assigns an expected sewing time or "standard" (in minutes) for each operation such that the amount of effort required to sew a standard minute is equivalent across tasks. The standard, which typically ranges between 0.5 and 2.0 minutes per operation, makes comparison of productivity across tasks and garments feasible and represents the central measure against which productivity is evaluated. Seamstresses are paid based on individual piece rates according to the standard set for the operation they undertake. In addition to the piece rate standard, workers also receive an hourly wage, or variance pay, when work is interrupted. Variances include the lack of work, machine breakage, job transfer, extra handling other than specified in the prescribed method, rework for which the seamstress is not responsible, making samples, and jury duty.

Module Production

In the winter of 1994 the plant manager began experimenting with the use of flexible work teams known in the garment industry as module production. The general manager handpicked the first team. The manager began to rely on module production in earnest by setting up eight teams in 1995. However, instead of hand picking teams, he asked for volunteers. After joining a team, seamstresses could return to PBS production if they preferred it or if other team-members voted a worker off the team. This option was available until mid-1996 when the manager decided to convert the entire plant to module production. When initially interviewed in the fall 1995, the manager had no plans to convert the entire plant to module production.

In module production at Koret each team typically is comprised of six or seven team-members who work in a U-shaped work space approximately 12' x 24'. Contiguously located around the partitioned workspace are 10 to 12 sewing machines mounted on wheels so that the ordering of machines is easily changed.[8] Also, workers are cross-trained on all sewing machines.

Seamstresses in modules are compensated with a group piece rate—the team receives a piece rate for the entire garment as opposed to a piece rate for each operation. The team's net receipts are divided equally. Group piece rates for modules have two additional differences from individual piece rates. First, each worker on the floor must unbundle and bundle the stack of garments when it arrives and leaves the workstation. Bundling and unbundling time accounts on average for five percent of the standard time for sewing an entire garment and is included in the PBS standard. The standard for an entire garment is five percentage points lower for modules because of the elimination of intermediate unbundling and bundling steps, which means that teams should be able to increase garment production by 5%, ceteris paribus. However, worker productivity of PBS and module production is measured in comparison to standard minutes, not garments, meaning that worker productivity measures for each are directly comparable. Second, whereas floor workers receive variance wages averaging approximately 10 to 12% of standard, module team-members receive no such variance wages. Instead, team-members receive piece-rate wages approximately 11% above the module-adjusted standard, which provides a small increase in incentive intensity. Quality, which the plant manager stated was at least as good and

[8] A variety of different sewing machines, which are specialized for different types of operations, exist.

perhaps better than quality provided by PBS production, is monitored upon completion of the garment using same inspection method found in PBS production.[9]

While modules essentially use the same labor, capital, and material inputs as PBS production, modules differ in that the team is empowered to make an array of production decisions. Workers reported that they could produce faster with higher quality in modules. They claimed they learned all production tasks, had more information about production tasks, and were able to shift tasks, share tasks, and "figure our easier ways to sew" garments. They stated that they found working in a team to be more interesting and fun, they enjoyed the friendships they developed in the team, and they preferred standing to sitting because it avoided backaches. They reportedly pushed each other to work hard, which often involved joking around. They also stated that other team members quickly caught quality problems, which allowed the team to quickly identify and correct the source of these problems. Team members claimed that the biggest difficulty of module production is that workers hold a "variety of attitudes", which can lead to "communication problems and misunderstandings". The manager added that workers were more aggressive than management at disciplining team-members.

3. The Koret Data

The data consists of weekly information on worker pay, hours worked, and team membership for all individuals employed at Koret from January 1, 1995 until December 31, 1997. In addition, the ethnicity and birth date of each worker was obtained, although further data on education, training, and so forth was not available to us. Finally, productivity is measured at the individual level when the worker is operating under the PBS system and at the

[9] HNO (2003) provides a more complete description of the PBS and module production systems used at Koret.

team level for workers engaged in module production. The productivity variable is measured as efficiency relative to the standard described above, with values greater than 100 indicating performance above the standard level.

Figure 3 plots the fraction of plant workers engaged in team production as well as median weekly productivity at the plant from the first week of 1995 (week 0) to the last week in 1997 (week 156). The figure shows that median productivity at Koret increases after the bulk of Koret workers are working in teams after week 70. However, the plot also shows substantial cyclical variation in productivity, which is accounted for by the inclusion of month and year dummies in the subsequent regression analysis. Table 1 presents summary statistics for the team-week data, indicating substantial variation in weekly team productivity across teams and over the 1995-1997 period. 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. Finally, there appears to be substantial variation in the ethnic composition of teams at the firm.

Measuring Diversity in Teams

The model in Section 1 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 other less able members and through knowledge transfer. Similarly, the least able member may gain substantial help from other members and learn 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. This ratio also is a reasonable measure of diversity in estimating the impact on turnover because the most able and the least able workers are the ones that are 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 affect communication among individuals. For example, one might argue that communication may be more difficult between a 20 and 25 year old than between a 40 and 45 year old.[10] Our second measure of demographic diversity considers the ethnic/racial composition of the team. Nine ethnic/racial groups are represented at Koret.[11] 54% of the workers are Hispanic, followed by 12% who are Vietnamese. More importantly, the only ethnically homogenous teams are Hispanic, and virtually all the teams that have at least two-thirds of team members belonging to the same ethnic group are largely Hispanic. Given that this group shares a common language, Spanish, we measure ethnic/racial diversity of each team by the fraction of the team that is Hispanic.

4. Diversity, Team Formation, and Turnover

In this section, we examine how workers sort themselves into teams when they are initially formed, and then examine the relationship between team characteristics and turnover. Our model suggests that workers may choose to form 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, peer pressure, and discrimination

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[10] Leonard and Levine (2002a) argue that the standard deviation of ln(age) provides a better measure of social distance than the standard deviation of age.

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

costs.

Initial Team Formation

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. The table also compares actual team characteristics with the characteristics of simulated teams randomly formed from workers in the firm. We construct these simulated teams by drawing 1000 teams of a particular size (e.g., 7 members) from the employees of the firm including those already in teams as of a particular date.[12] The characteristics of these simulated teams are recorded, and the mean and 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 on 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. In particular, teams 2, 3, and 7, which consist of relatively less able workers, have the greatest diversity in individual productivity. By contrast, teams formed in 1996 and 1997, when team participation was generally 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

[12] Because workers could switch teams without penalty and such turnovers were not rare, including the workers already in teams in our simulations is appropriate.

inability of these teams 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 teams 3 and 20 are initially formed with all Hispanic workers, and teams 9 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.[13] 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) indicate 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.[14]

Diversity and Turnover

Our model suggests that 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,

[13] The non-Hispanic members of teams with less than half Hispanic employees come from two or more of the ethnic groups working at Koret.

[14] 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

these factors may directly influence utility through peer pressure effects or preferences for working with particular groups of co-workers. To analyze the impact of diversity on turnover at Koret, we construct team employment 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 355 spells of team participation. Figure 4 shows the fraction of founding team members remaining on the team at the end of our sample period. Team membership is surprisingly stable. For example, 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. In some cases, workers from these teams left the firm altogether, while others joined another team at Koret, sometimes as a founding member.

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 ($r = e$).[15] Very few workers leaving a team return to individual production, so the vast majority of $r = e$ exits represent an employee leaving the firm completely.

Figure 5 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. 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 Figure 5 is that match

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their early twenties from a range of ethnic backgrounds (as judged by the workers' names). Because no pre-team productivity data is available, Team 21 is excluded from the team regressions reported in Table 3 and 4 below.

[15]The empirical transition intensity is defined as $\lambda_r(\tau)$ = (number of job spells lasting exactly τ weeks and ending for reason r)/(number of job spells lasting at least τ weeks).

quality or 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 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* associated with leaving team *j* after τ weeks at calendar date *t* for reason *r*, $\lambda_r(\tau)$, follows a proportional hazards specification:

$$\lambda_r(\tau \mid X_{1jt}, X_{2jt}, X_{3jt}, Z_{ijt}, W_t) = \exp(X_{1jt}\gamma_r + X_{2jt}\mu_r + X_{3jt}\pi_r + Z_{ijt}\rho_r + W_t\omega_r)\lambda_{0r}(\tau), r = e, o, \quad (4.1)$$

where the time varying vector 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 indicators of whether the team consists of two-thirds Hispanic employees, or whether all the workers on the team were Hispanic. X_{3jt} includes variables thought in the literature to affect team productivity: team size (*SIZE*); a cubic polynomial in the length of time the team has been in operation (*TEAM TENURE*); and variables accounting for seasonality in Koret's production that might affect employment.[16] The vector Z_{ijt} includes worker *i*'s individual characteristics, in most cases

[16] 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 6 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.

measured relative to the team j average at date t.[17] 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.[18]

Table 3 presents three pairs of Cox proportional hazard estimates for the duration model outlined above. A positive coefficient indicates that an increase in the variable is associated with an increase in the transition intensity. The base specification estimates are shown in columns (1) and (4) for the conditional probability of leaving the team to exit the firm and switching teams, respectively. Following studies such as Leonard and Levine (2002b), we measure individual isolation on the team as the absolute value of the distance between the worker's characteristics and the average of those for the team. We also distinguish whether the worker was above or below the team average, due to potential asymmetries in response implied by our theoretical model.

The coefficient estimates of the skill and demographic variables in our base specification reflect the impact of these factors on both team productivity and pay, as well as peer pressure and worker preferences. The specification in columns (2) and (5) attempts to separate these effects by including a covariate measuring lagged team productivity and indicating whether the

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[17] There may be some concern about the potential endogeneity of the X_{1jt} and X_{2jt} variables as they vary over the course of the spell. We re-estimated the models shown in Table 3 measuring the covariates included in X_{1jt} and X_{2jt} at the time the worker joined the team. This approach yields very similar results to those reported in Table 3.

[18] From Table 2, we define a set of dummy variables indicating whether period τ of the spell fell during: (a) weeks 32 to 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.

worker's ability was above or below team productivity.[19] Holding team productivity constant, the demographic variables are likely to reflect preferences toward working with similar individuals. In addition, 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.[20] Our third specification in columns (3) and (6) includes indicators of whether the worker was most skilled (Max on Team) or least skilled (Min on Team) on the team, interacted with the difference between the worker's production and the team average. These variables assess the prediction that the most productive member of the team will be more likely to switch teams in order to increase her income. Moreover, it may be the case that the most able team member is more subject to being poached away by other teams at Koret. For the least able member on the team, two factors may be at work. The worker will want to stay on the team because she gains substantial monetary benefit from team membership. However, she may be subject to intense peer pressure and hence be more likely to leave the firm.

We first focus on the team level variables across all specifications reported in Table 3. The estimates of the base specification in columns (1) and (4) indicate that workers are less likely to leave the firm or switch teams if they are on a team with more productive workers, on average. However, after including lagged team productivity in the model, the results in columns (2) and (5) suggest that this reflects the fact that teams with more able members are more productive. In fact, columns (5) and (6) show that the most productive and highly paid teams are

[19] 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.

[20] 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.

more likely to stay intact, since members are less likely to defect to other teams. Skill diversity appears to be unrelated to workers exiting Koret but is positively related to workers switching teams. If such teams are more productive (as we show in the next section) other teams may infer that members have high collaborative skills (HNO (2003) and attempt to poach them. Ethnic diversity reduces the transition probability of exit for teams with two thirds Hispanic (no exits occurred among individuals on all Hispanic teams) and also reduces the transition probability of switching teams for the all Hispanic teams but not for 2/3 Hispanic teams. Given that the results persist after the inclusion of lagged team productivity, these findings are consistent with worker preferences for segregation, as suggested by Becker (1957).

Focusing on individual variables in the bottom panel of Table 3, workers whose skills are above the team average or the team productivity level are more likely to switch teams, but the coefficient estimates are not statistically significant. Similarly, there is no evidence that more "isolated" team members, either in terms of age or ethnicity, are more likely to leave the team. The only consistently statistically significant result is that Hispanics are less likely to exit the firm, although, somewhat surprisingly, this effect is moderated by being in the majority on a two-thirds Hispanic 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, although support is found for the view that some workers prefer homogeneous groups. The coefficient estimates also indicate the most highly skilled worker is not significantly more likely to switch teams, either due to poaching or the desire to increase her income and the least skilled worker is not significantly more likely to leave Koret. A key driver of turnover appears to be the productivity (and the resulting pay) of the team. The most productive teams are more likely to remain intact than less productive teams.

To the extent that peer pressure exists in teams at Koret, the negative effect on utility may be offset by the positive impact on team productivity.

5. 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, when highly productive workers can substantially increase the production of the least able workers on the team by helping, teaching or coordinating activities (*e.g.,* Σf_i increases with skill diversity). 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. 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.

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:

$$y_{jt} = X_{1jt}\alpha + X_{2jt}\beta + X_{3jt}\delta + \varepsilon_{jt} \qquad (5.1)$$

where X_{1jt}, X_{2jt}, and X_{3jt} are as defined in Section 4, with the exception that X_{3jt} also includes an indicator of whether the team includes a new hire with no previous Koret experience (*NEWHIRE*). To account for possible selection effects, a variable indicating that the team was formed in April 1996 or later (*LATER TEAM*) is also included. 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 equation (5.1), shown in the first column of Table 4, exhibit four notable features. 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. This result holds in our median regression model shown in column (2) that is more robust to outliers in the dependent variable. The positive estimated relationship between the spread in skill and productivity is consistent with the case of the high value of collaborative effort in the model in Section 1, which argued that a team with a greater spread in ability will be more productive when there is substantial learning and task coordination. Moreover, HNO (2003) suggest that the most skilled workers may be able to increase the team norm level of output by threatening to quit the team.

The coefficient estimate in the fourth row of column (1) indicates that teams with more diversity in age are significantly less productive. This finding is consistent with Leonard and Levine (2002a), 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 firm 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 et al. (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.

Estimates of our second measure of demographic diversity, the team's ethnic composition, provides mixed support for the view that demographically homogeneous teams have lower communication costs that lead to higher productivity. Column (1) shows that teams comprised entirely Hispanics are 11.5% more productive than more ethnically diverse teams at Koret. However, the magnitude and significance of this coefficient estimate falls in the median regression in column (2). Moreover, teams of two-thirds or more Hispanic members (e.g., a six person team with four or five Hispanic members) are no more productive than more diverse teams.

One concern about the estimates described above is that there are unobserved team characteristics correlated with the diversity measures that also affect productivity. To account for the potential confounding role of team-level unobserved factors, we estimate fixed effect models of equation (5.1). In most cases, a change in the team roster involves the replacement of one worker, rather than wholesale changes in the team. Consequently, the impact of diversity on productivity is identified by relatively marginal changes in the composition of a team that may already have set routines and communication patterns.

After including team fixed effects in the regression, column (3) of Table 4 shows that increasing the average skill level of the team increases productivity, as was the case in the OLS and median regressions. Moreover, increasing the skill diversity of the team, holding the average constant, continues to positively affect team productivity, although the impact is moderated somewhat by the inclusion of the team fixed effects. On the other hand, the coefficient estimates of the demographic diversity measures shown in column (3) do not appear to be robust to the inclusion of team fixed effects. The estimated impact of diversity in the age of team members becomes positive but insignificant, while the productivity of teams composed solely of Hispanics is not significantly different from that of more ethnically diverse teams. In fact, teams comprised of two-thirds or more (but not all) Hispanics are actually less productive than more diverse teams once team dummies are included in the model. Overall, the results from

Table 4 suggest that skill diversity raises team productivity, which is consistent with the observation that there is substantial learning and coordination at Koret and 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.

6. Discussion and Conclusion

Team work is a central feature of 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, and Gant (2003)). This paper assesses the "business case for diversity" by examining the effects of various dimensions of team member diversity on productivity in production teams by first developing a formal model linking various types of diversity to team-member turnover and team productivity in a production setting. The model shows that diversity in ability enhances the 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 model explains the impact of both skill and demographic diversity in the same framework, which we then use to interpret our data.[21]

Based on the implications of our theoretical model, we use a novel data set from a

[21] The model offers a new prediction not found in the literature. Any level of team norm is an equilibria when team-members are homogeneous in ability. The model predicts that the range of equilibria decreases as teams become more homogenous. Unfortunately, our data is insufficient to test this additional implication.

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. Our results indicate that teams with more heterogeneous worker abilities are more productive. On the other hand, holding the distribution of team ability constant, teams with greater diversity in age are less productive, and those composed only of one ethnicity (Hispanic workers in our case) are more productive, but the findings for team demographics are not robust to alternative model specifications. Turnover costs associated with diversity appear to be modest, since the most productive teams are more likely to remain intact. It is the case that workers on all Hispanic teams are less likely to leave the team, even after accounting for team productivity, indicating some preference for segregation among these workers.

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.

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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[1]	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	

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

TABLE 2
INITIAL TEAM CHARACTERISTICS AND AVERAGE WEEKLY TEAM PRODUCTIVITY, ACTUAL AND RANDOMLY FORMED TEAMS

Team	Date of Team Formation	Mean Individual Productivity[1] (1)	Max/Min Individual Productivity (2)	Mean ln(Age) (3)	S.D. of ln(Age) (4)	Fraction Hispanic (5)	Fraction with Prior Team Experience (6)	Team Productivity (Weeks 21+)[2] (7)
				Teams Formed 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 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 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 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
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	-[3]	-	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 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 1000 simulated teams formed randomly from the workers at the firm as of the given date. Entries in brackets represent 5th and 95th percentiles.

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

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

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

TABLE 3
COX TRANSITION INTENSITY ESTIMATES FOR LEAVING TEAM

	Exit Event					
	Leaves Firm			Switches Teams		
	(1)	(2)	(3)	(4)	(5)	(6)
Team-Level Variables						
Avg. Prod.	-0.017	-0.009	-0.010	-0.018	-0.004	-0.001
	(0.012)	(0.012)	(0.011)	(0.008)	(0.011)	(0.011)
Ratio of Max/Min Prod.	-0.021	0.025	0.016	0.112	0.207	0.249
	(0.191)	(0.181)	(0.180)	(0.098)	(0.107)	(0.108)
Mean ln(Age)	0.375	0.044	0.081	-0.473	0.026	0.075
	(1.627)	(1.417)	(1.410)	(1.085)	(1.100)	(1.106)
S.D. ln(Age)	-0.385	0.104	0.141	0.977	0.820	0.779
	(2.978)	(3.025)	(3.007)	(1.543)	(1.577)	(1.574)
All Hispanic Team	-	-	-	-2.039	-1.913	-1.894
				(0.731)	(0.770)	(0.758)
2/3 Hispanic Team	-1.456	-1.321	-1.297	-0.726	-0.487	-0.494
	(0.698)	(0.656)	(0.659)	(0.502)	(0.532)	(0.531)
Team Productivity[1]		-0.012	-0.011		-0.013	-0.015
		(0.011)	(0.011)		(0.007)	(0.006)
Individual Variables						
|Individual – Avg Prod.|	0.004			0.010		
Above Avg. Prod.	(0.011)			(0.007)		
|Individual – Avg Prod.|	0.009			0.003		
Below Avg. Prod.	(0.014)			(0.007)		
|Individual – Team Prod.|		-0.003			0.006	
Above Team Prod.[2]		(0.007)			(0.005)	
|Individual – Team Prod.|		-0.001			0.003	
Below Team Prod.[3]		(0.012)			(0.006)	
|Individual – Avg. Prod.|			-0.006			0.004
Max on Team			(0.010)			(0.007)
|Individual – Avg. Prod.|			0.002			-0.006
Min on Team			(0.013)			(0.007)
|Individual – Mean ln(Age)|	-0.480	-0.431	-0.439	-0.428	-0.352	-0.300
	(1.178)	(1.180)	(1.185)	(0.717)	(0.769)	(0.765)
Individual is Hispanic	-1.610	-1.480	-1.482	0.321	0.362	0.391
	(0.601)	(0.607)	(0.588)	(0.238)	(0.247)	(0.257)
Hispanic on 2/3 Hispanic Team	1.264	1.062	1.052	0.126	-0.024	-0.034
	(0.940)	(0.920)	(0.923)	(0.539)	(0.545)	(0.552)
Log-Likelihood	-164.1	-158.9	-158.9	-539.1	-491.6	-491.8

Note: Based on N = 355 Worker-Team Spells. Robust Standard Errors in Parentheses. Each model includes a cubic polynomial in team tenure, indicators for whether the team was formed in April 1996 or later, whether the worker was a team founder, and the week during sample period as defined in footnote 13, month dummies, and cyclical variables measuring women's retail garment sales.

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

[2]Variable is the value of Individual – Team Productivity if it is positive, zero otherwise.

[3]Variable is the (absolute) value of Individual – Team Productivity is negative, zero otherwise.

TABLE 4
EFFECT OF TEAM COMPOSITION ON TEAM PRODUCTIVITY
Dependent Variable is ln(Productivity$_{it}$) For Team in Each Week

Variable	Specification		
	OLS (1)	Median (2)	Fixed Effects (3)
Average Productivity	0.004	0.004	0.005
	(0.0017)	(0.0019)	(0.0014)
Ratio of Max/Min	0.057	0.051	0.030
Productivity	(0.016)	(0.020)	(0.016)
Mean ln(Age)	0.099	0.192	-0.137
	(0.196)	(0.240)	(0.161)
S.D. ln(Age)	-0.438	-0.446	0.077
	(0.213)	(0.281)	(0.216)
All Hispanic	0.115	0.079	-0.047
	(0.069)	(0.149)	(0.082)
2/3 Hispanic	-0.018	-0.001	-0.152
	(0.044)	(0.061)	(0.049)
SIZE	0.007	-0.0003	0.007
	(0.019)	(0.019)	(0.014)
NEWHIRE	-0.025	-0.018	0.066
	(0.041)	(0.046)	(0.037)
LATER TEAM	-0.089	-0.094	-
	(0.074)	(0.089)	

Note: N = 2012 observations. Standard errors in parentheses. Standard errors adjusted to account for clustering by team. Robust standard errors for OLS and Fixed Effect regressions. Standard errors for median regressions are block bootstrapped with 500 replications. Each regression also includes a constant, a cubic polynomial in team tenure, dummies for each month, and cyclical variables measuring women's retail garment sales.

Appendix: Proof of Proposition 1

Assume $c_1 < c_2 < ... < c_N$ without loss of generality. From Lemma 1,

$$e_i^* = \min(c_i(\frac{w}{N} f_i + k),\ \max(\frac{wc_i f_i}{N}, m)).$$

Note that e_i^* is a continuous function of *m* and nondecreasing in *m*. Hence, $M(m) = \sum_{i=1}^{N} e_i^*$ also has the same property. Because *M*(*m*) is bounded, the fixed point that satisfies $M(m^*) = m^*$ always exists.

When $\frac{wc_N f_N}{N} < c_1(\frac{wf_1}{N} + k)$, $e_i^* = m$ for all *i* for any $m \in [\frac{wc_N f_N}{N},\ c_1(\frac{wf_1}{N} + k)]$.

Therefore, any number in this range is the fixed point and therefore an equilibrium team norm. When $\frac{wc_N f_N}{N} \geq c_1(\frac{wf_1}{N} + k)$, however, *M*(*m*) is determined uniquely and differentiable almost everywhere. Because $\frac{dM}{dm} < 1$ almost everywhere, *M*(*m*) crosses the 45 degree line only once and thus has only one fixed point. Therefore, there exists a unique equilibrium.

FIGURE 1: OPTIMAL EFFORT CHOICE GIVEN TEAM NORM M^*: VERY HOMOGENEOUS TEAM

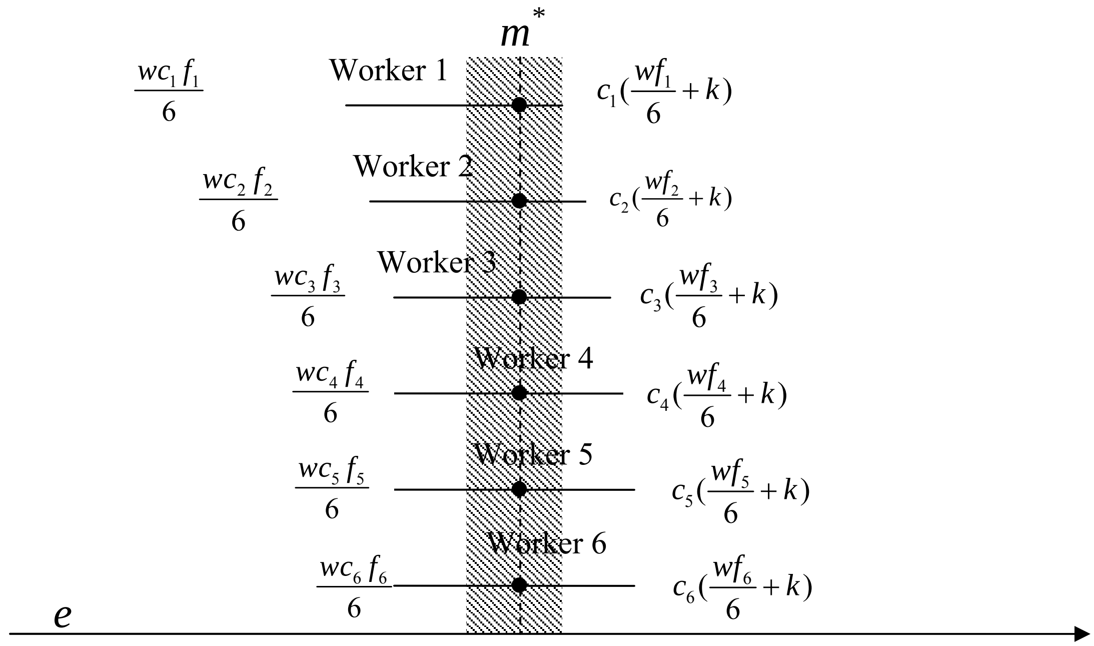
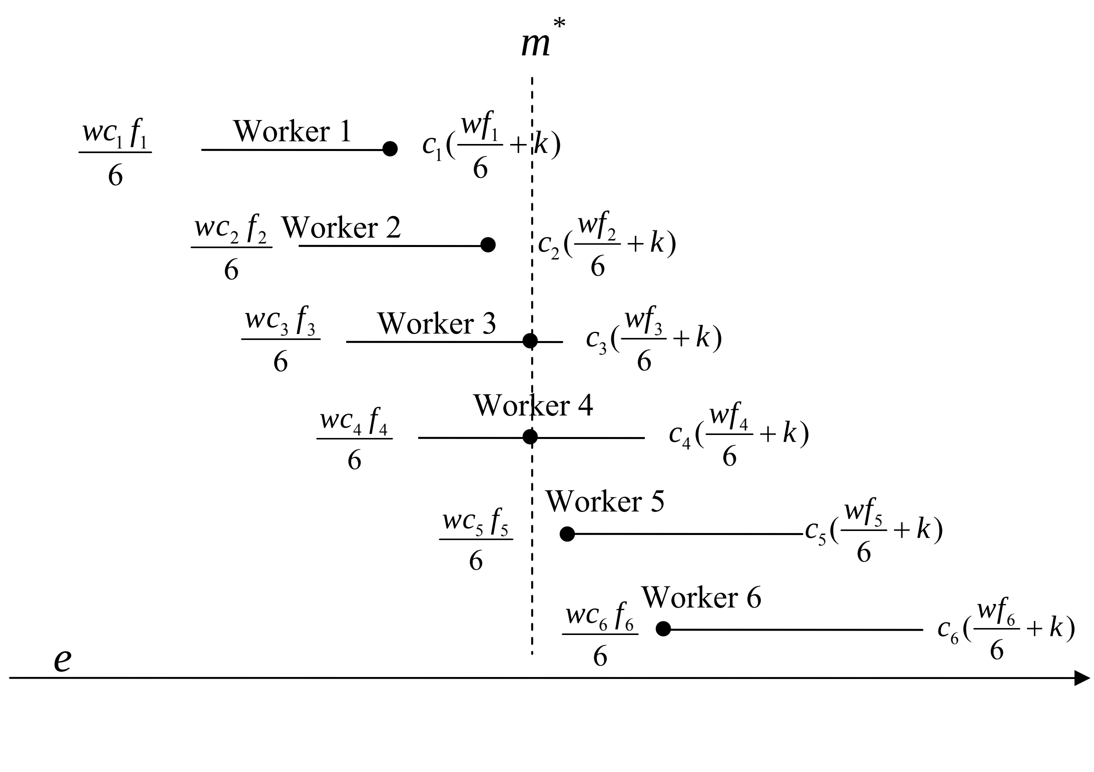


FIGURE 2: OPTIMAL EFFORT CHOICE GIVEN TEAM NORM M^*: VERY HETEROGENEOUS TEAM



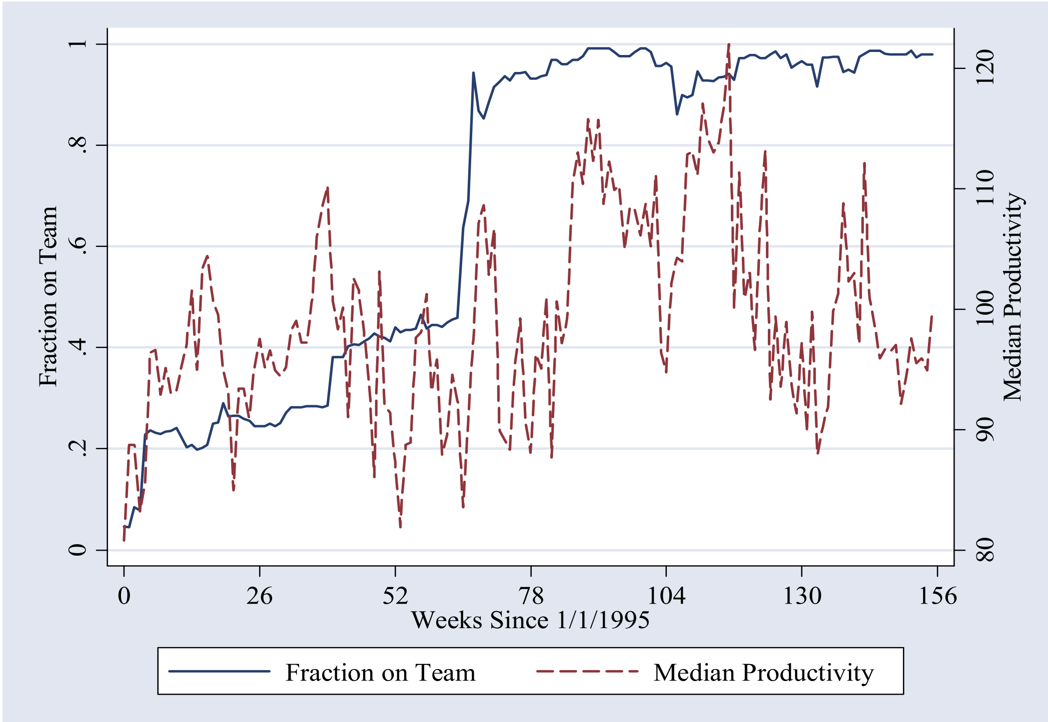


FIGURE 3: FRACTION OF WORKERS ON TEAMS AND MEDIAN TEAM PRODUCTIVITY

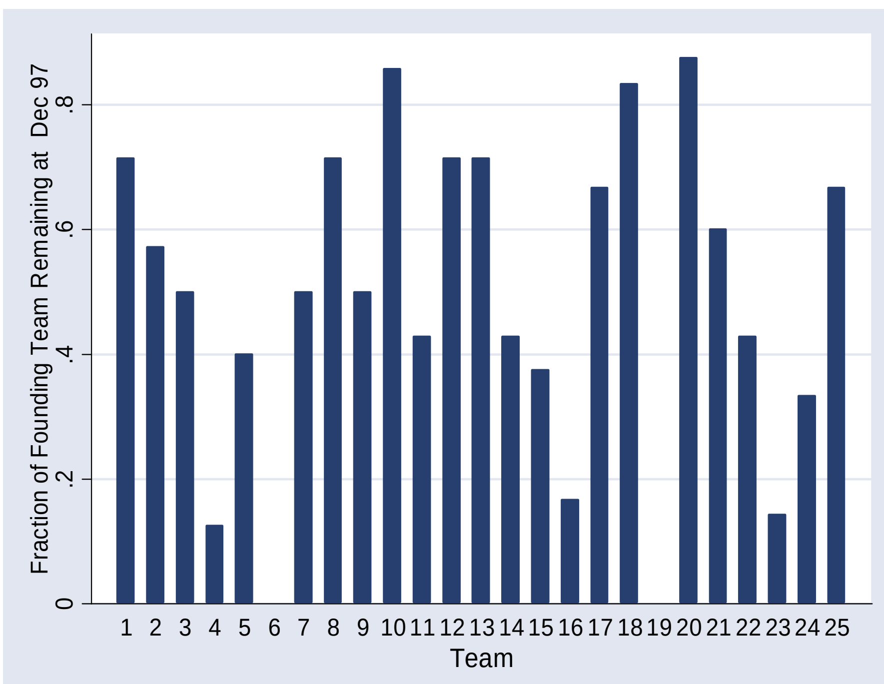


FIGURE 4: FRACTION OF FOUNDING TEAM MEMBERS REMAINING AS OF 12/31/97

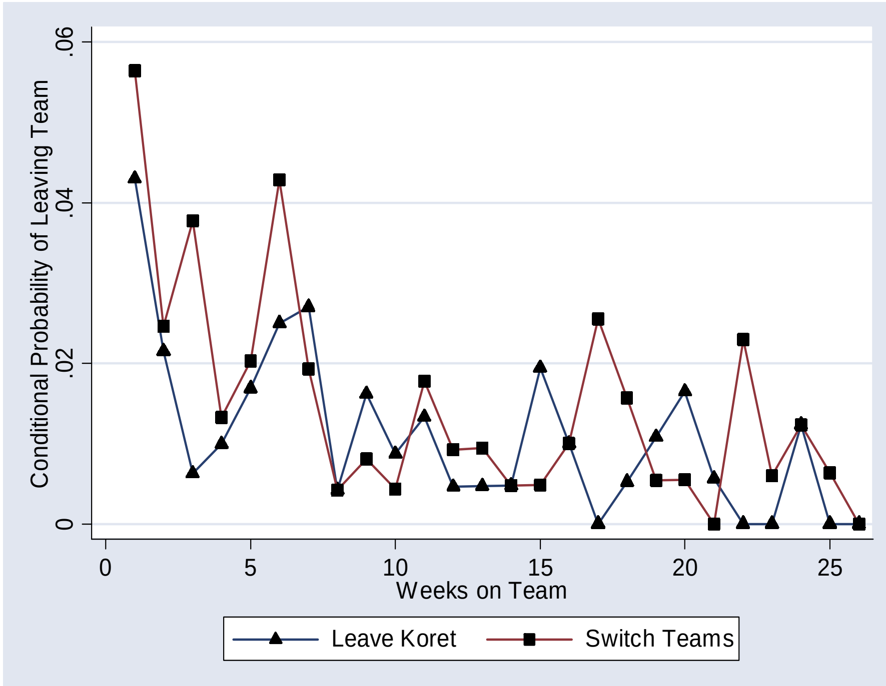


FIGURE 5: EMPIRICAL TRANSITION INTENSITIES