Ethnic Divisions and Production in Firms

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Abstract

A body of literature suggests that ethnic heterogeneity limits economic growth. This paper provides microeconometric evidence on the direct effect of ethnic divisions on productivity. In team production at a plant in Kenva, an upstream worker supplies and distributes flowers to two downstream workers who assemble them into bunches. The plant uses an essentially random rotation process to assign workers to positions, leading to three types of teams: (a) ethnically homogeneous teams, and teams in which (b) one or (c) both downstream workers belong to a tribe in rivalry with the upstream worker's tribe. I find strong evidence that upstream workers undersupply non-coethnic downstream workers (vertical discrimination) and shift flowers from non-coethnic to coethnic downstream workers (horizontal discrimination), at the cost of lower own pay and total output. A period of ethnic conflict following Kenya's 2007 election led to a sharp increase in discrimination, which did not decay in the nine months after conflict ended. In response, the plant began paying the two downstream workers for their combined output (team pay). This led to a modest output reduction in (a) and (c) teams – as predicted by standard incentive models – but an *increase* in output in (b) teams, and overall. Workers' behavior before conflict, during conflict, and under team pay is predicted by a model of taste-based discrimination. My findings suggest that inter-ethnic rivalries lower allocative efficiency in the private sector, that the economic costs of ethnic diversity vary with the political environment, and that in high-cost environments firms are forced to adopt "second best" policies to limit discrimination distortions.

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1. Introduction

There is evidence to suggest that ethnic heterogeneity may impede economic growth. A negative influence on decision-making in the public sphere has been documented: public goods provision is lower and macroeconomic policies of lower quality in ethnically fragmented societies (Easterly and Levine, 1997; Alesina and Spolaore, 1997; LaFerrara, 2003; Miguel, 2004). The possibility of an additional *direct* effect on productivity in the private sector has long been recognized, however. Individuals of different ethnicities may have different skill-sets and therefore complement each other in production, but it is also possible that workers of the same ethnic background collaborate more effectively (Lang, 1986; Lazear, 1998). Evidence from poor countries on the productivity effects of ethnic diversity is largely absent.

This paper provides novel microeconometric evidence on the productivity effects of ethnic divisions. I identify a negative effect of ethnic diversity on output in the context of joint production at a large plant in Kenya where workers were quasi-randomly assigned to teams. I then begin to address how output responds to increased conflict between ethnic groups, how firms respond to lower productivity in diverse teams, and how workplace behavior responds to policies implemented by firms to limit ethnic diversity distortions. A model of taste-based discrimination at work explains my findings across these dimensions.

I study a sample of 924 workers working in teams at a plant in Kenya. The workers package flowers and prepare them for shipping: productivity is observed and measured by daily individual output. The effects of ethnic divisions are of particular importance in the Kenyan context. Tribal competition for political power and economic resources has been a defining character of Kenyan society since independence (Ndegwa, 1997; Oyugi, 1997; Barkan, 2011). Workers at the flower plant are almost equally drawn from two historically antagonistic ethnic blocs - the Kikuyu (and allied tribes) and the Luo (and allied tribes).

Production takes place in triangular packing units. One upstream "supplier" supplies and arranges roses that are then passed on to two downstream "processors" who assemble the flowers into bunches, as illustrated in figure 1a. The output of each of the two processors is observed. During the first period of the sample, processors were paid a piece rate based on own output and suppliers a piece rate based on total team output. Inefficiently low supply of roses to downstream workers of the rival ethnic group was thus costly for suppliers.

I show that the plant's system of assigning workers to positions through a rotation process generates quasi-random variation in team composition. A worker's past productivity and observable characteristics are orthogonal to those of other workers in her assigned team. The productivity effect of ethnic diversity can thus be identified by comparing the output of teams of different compositions.

Two natural experiments during the time period for which I have data allow me to go further. During the second period of the sample, in early 2008, contentious presidential election results led to political and violent conflict between the Kikuyu and Luo ethnic groups, but production at the plant continued as usual. In the third period of the sample, starting six weeks after conflict began, the plant implemented a new pay system in which processors were paid for their combined output ("team pay"). By taking advantage of the three periods observed, I identify (a) the source of productivity effects of ethnic diversity in the context of plant production in Kenya; (b) how the economic costs of ethnic diversity vary with the political and social environment; and (c) how managers responded to ethnic diversity distortions at the plant, and how workplace behavior changed as a consequence of the policies implemented in response.

I model ethnic diversity effects as arising from a "taste for discrimination" among upstream workers: suppliers attach a potentially differential weight to coethnics' and non-coethnics' utility, a formulation that follows Becker (1974), Charness and Rabin (2002) and others. The model predicts that discriminatory suppliers in mixed teams will "misallocate" flowers both vertically - undersupplying downstream workers of the other ethnic group - and horizontally - shifting flowers from non-coethnic to coethnic downstream workers.¹ The impact of horizontal misallocation on total output will depend on the relative productivity of favored and non-favored downstream workers. If conflict led to a decrease in non-coethnics' utility-weight, a differential fall in mixed teams' output in early 2008 is predicted. Under team pay, a positive output effect of a reduction in horizontal misallocation is expected to offset negative freeriding effects, in teams in which the two processors are of different ethnic groups. The reason is that suppliers can no longer influence the relative pay of the two processors through relative supply under team pay.

Quasi-random assignment led to teams of three different ethnicity configurations. About a quarter of observed teams are ethnically homogeneous, another quarter are "vertically mixed" teams in which both processors are of a different ethnic group than the supplier, and about half are "horizontally mixed" teams in which (only) one processor is of a different ethnic group than the supplier. The ethnicity configurations are displayed in figure 1b. I test the model's predictions by comparing the average output of teams of different ethnicity configurations within and across the three sample periods.

In the first main result of the paper, I find that vertically mixed teams were eight percent less productive and horizontally mixed teams five percent less productive than homogeneous teams during the first period of the sample. The output gap between vertically mixed and homogeneous teams points to vertical discrimination: it appears that upstream workers are willing to accept lower own pay in order to lower the pay of non-coethnic co-workers. About 86 percent of the output gap between horizontally mixed and homogeneous teams is due to vertical misallocation and 14 percent due to horizontal misallocation. Because Kikuyu and Luo workers are of similar productivity on average, horizontal misallocation has little impact on total output. But the distribution of output across downstream workers is affected: in horizontally mixed teams, processors of the supplier's ethnic group earn 27 percent more than processors of the other ethnic group.

In the second main result of the paper, I find that the output gap between homogeneous and diverse teams nearly doubled when conflict between the Kikuyu and Luo political blocs began in early 2008. The reason appears to an increase in workers' taste for ethnic discrimination. I estimate

¹Unless otherwise specified, I use "coethnic" to indicate a processor of the supplier's tribal bloc, and "noncoethnic" to indicate a processor who is not of the supplier's tribal bloc. I also use "upstream worker" and "supplier" synonymously, and "downstream worker" and "processor" synonymously.

a decrease of approximately 35 percent in the utility-weight of non-coethnic co-workers when conflict began, through a reduced form approach. As also predicted by the model, there was a small but significant increase in the output of processors of the supplier's ethnic group in horizontally mixed teams in early 2008. A back-of-the-envelope calculation suggest that the decrease in productivity in mixed teams may have cost the farm half a million dollars in annual profit, had it not responded. It is clear from these results that the economic costs of ethnic diversity vary with the political environment.

In the third main result of the paper, I find that the introduction of team pay for processors six weeks into the conflict period led to an increase in output in horizontally mixed team, returning the difference in output between homogeneous and horizontally mixed teams to pre-conflict levels. The increase was likely due to a reduction in horizontal misallocation: a 32 percent output gap between coethnic and non-coethnic processors in horizontally mixed teams was eliminated when team pay was introduced, as predicted by the model. As a result, overall output increased, even though there was a modest decrease in output in homogeneous and vertically mixed teams. These results indicate that that firms are forced to adopt "second best" policies to limit the distortionary effects of ethnic diversity in the workforce when taste for discrimination is high enough. Figure 2 illustrates the evolution of output in teams of different ethnicity configurations during each of the three sample periods observed.

This paper's findings have important implications for theory and policy. Distortionary, tastebased discrimination in production appears to be the primary explanation behind my results. Theories of non-taste-based ethnic diversity effects are unlikely to simultaneously explain a differential fall in mixed teams' output during conflict and equalization of downstream workers' output under team pay. Distinguishing between different channels through which ethnic diversity may affect productivity is important. Higher output in homogeneous teams may be *efficient* if due to technological differences across diverse and homogeneous teams. But discriminatory preferences should lead to distortionary misallocation of resources in most joint production situations in which individuals influence the output and income of others. Interacting economically with individuals of other ethnic backgrounds is hard to avoid when urbanization and economic modernization brings larger groups of workers together, and large multiplier effects are associated with misallocation of intermediate goods (Jones, 2011). The contribution of taste-based discrimination in production to the lower incomes observed in diverse countries may thus be sizable.

The findings of this paper also suggest that relatively brief episodes of conflict can have a longlasting impact on distortionary attitudes towards individuals of other groups. I find no reversion in ethnic discrimination in the nine months after conflict ended. It appears that the economic costs of ethnic diversity vary with the political environment because social preferences are affected by conflict, forcing firms to adjust their policies in conflictual environments. Entirely removing incentives to discriminate through contractual design is difficult, however. At the plant, biased upstream workers continued to derive less benefit from flowers supplied to pairs of processors that included non-coethnics under team pay. As a consequence, it appears, output in vertically mixed teams was 15 percent lower than in homogeneous teams after team pay was introduced.

This paper contributes to and ties together several areas of research. Its results are to my knowledge the first to carefully identify and explain a negative effect of ethnic diversity on productivity in the private sector, perhaps because well-measured, micro-level output data from poor countries is rarely available.² By showing that a taste for ethnic discrimination can lower output by leading to misallocation of intermediate goods, I also contribute to the literature on workplace favoritism initiated by Becker (1957) and the recent literature on social preferences at work (Bandiera et al., 2005, 2009; Mas and Moretti, 2009). The difference between the findings of Bandiera et al. (2009) in the U.K. and my findings in Kenya are particularly interesting. The authors find that "upstream" supervisors at a fruit farm in the U.K., in their allocation of own effort and in their assignment of "downstream" workers to rows with different amounts of fruit, discriminate against workers to whom they are not socially connected only when doing so is costless to the supervisor. In contrast, this paper documents an upstream willingness to pay to lower the incomes of nonfavored downstream workers, to my knowledge the first paper to do so in data on consequential choices made every day. Ethnic antagonism may be of greater importance to workers in Kenya than social (dis)connections are to workers in the U.K. Burgess et al. (2011) and LaFerrara (2002) show that Africans belonging to a different ethnic group than "upstream" decisionmakers have less access to economic resources in other contexts, suggesting that distortionary discrimination may be a common phenomenon in Africa.

If individuals have discriminatory *preferences*, output is likely to be lower in diverse production units in most production situations in which co-workers affect each other's income. I begin to address how the productivity effects of ethnic diversity are likely to vary across time and space by studying how workplace discrimination responds to increased ethnic conflict in society, and how firms respond to distortionary discrimination. I follow an innovative paper by Krueger and Mas (2004) in exploring worker behavior during conflict, but my focus is on a poor country characterized by frequent, ethnic tensions. I follow Ksoll et al. (2010) in studying Kenyan flower farms during the political crisis of 2008, but focus on the effect of conflict on distortionary attitudes towards non-coethnics. As such, this paper also adds to an emerging literature investigating how social preferences are shaped (Bauer et al., 2011; Jakiela et al., 2010).

How firms respond to distortions due to ethnic diversity and how to optimally organize production in the presence of discriminatory attitudes is an exciting venue for future research. Prendergast and Topel (1997) provides a theoretical analysis of the influence of favoritism on optimal compensation and extent of authority for managers. In studying the motivation behind the introduction of team pay at the plant, this paper is particularly related to LaFerrara (2002) who shows that ethnically diverse cooperatives are more likely to adopt group-pay. I also investigate why the plant

²There is a literature on the effects of demographic diversity in production in rich countries, although it consists primarily of theoretical work and descriptive empirical studies. Lazear (1998) provides an interesting theoretical discussion of the potential costs and benefits of diversity in joint production situations. Hamilton et al. (2005) analyzes the effects of diversity in joint production in a setting in which workers selected into teams as a factory in California switched from individual to joint production. See Alesina and LaFerrara (2005) for a survey of the literature.

chose not to segregate Kikuyu and Luo workers.

Finally, there are interesting connections between this paper's results on within-firm misallocation and the literature in macroeconomics on across-firm misallocation of capital and intermediate goods in poor countries (Banerjee and Moll, forthcoming; Hsieh and Klenow, 2009). First, some of the distortionary policies studied by macroeconomists may exist in part as a means for politicians to skew the distribution of resources towards their own ethnic groups and thus ultimately arise from biased preferences upstream. Second, firms whose output suffers from internal misallocation due to ethnic diversity distortions may survive due to macro-level misallocation of capital. Jones (2011) points out that to understand development we need to understand both why misallocation occurs and the intermediate goods and linkages through which its effects are amplified.

The paper is organized as follows. In section 2, I describe the setting and the organization of production at the plant, outline the data used, and test for systematic assignment to teams. The model of upstream discrimination is presented in section 3, and its predictions for the three sample periods observed tested in section 4. Section 5 explores the extent to which other ethnic diversity mechanisms may explain my results. Section 6 investigates the response of distortionary attitudes towards non-coethnics to conflict in more depth, and section 7 the plant's response to discrimination. Section 8 concludes.

2. The Setting

2.1 Ethnic diversity and floriculture in Kenya

Ethnic divisions have influenced Kenyan society and politics since independence and contributed to periodical violence. The country's biggest tribe, the Kikuyu, was favored by Kenya's British colonizers, a fact that has had long-lasting influence on tribal relations. The Kikuyu has also been the most economically successful and politically influential tribe during most periods of the post-independence era. Although the relationships between different tribes have varied over time, the other major tribes have typically defined themselves politically in opposition to the Kikuyu. In recent years the opposition has been led by the second biggest - and persistently politically active - tribe, the Luo. Most Kenyan tribes have aligned themselves with one of the two associated camps. I therefore categorize workers according to the tribal coalition ("ethnic group") to which their tribe is seen to belong - the "Kikuyu" (and associated tribes) and the "Luo" (and associated tribes).³

An interesting case study in the context of ethnic divisions is Kenya's vibrant floriculture sector, which brings together large numbers of workers of different backgrounds. A rapid expansion of the sector began in the 1980s; Kenya is now the third-largest exporter of flowers in the world and supplies approximately 31 percent of flowers imported into Europe (African Business, 2011). Around 50,000 Kenyans are employed in floriculture, and 500,000 in associated industries. Flower farms are part of the fastest growing sub-sector of the Kenyan economy (Kenya Flower Council, 2011). Production takes place on large farms that typically sell their product through auctions in

³I designate individuals of the Kikuyu, Embu, Meru, Kamba, Maasai and Kisii tribes as "Kikuyu" and those of the Luo, Luhya and Kalenjin tribes as "Luo", but focusing on individual tribes instead gives similar results - see section 4.

The Netherlands. Most flower farm employees work either in greenhouses (growing and harvesting) or packing plants (packing and preparing flowers for sale).

On some farms, including the one I focus on, workers reside on farm property in gated communities. Such farms essentially constitute a miniature society - complete with schools, health clinics and other amenities - in which groups of individuals from different ethnic backgrounds live and work together. Flower farm jobs are considered relatively desirable.

2.2 Organization of production at the plant

The sample farm primarily produces roses. Plant workers are roughly equally divided across three halls. Packing takes place in three-person teams, as depicted in figure 1a. One upstream "supplier" supplies two downstream "processors" working on separate tables. The supplier brings flowers arriving from the greenhouses to her worktable and throws out poor quality flowers. She then sorts flowers of different lengths/types into piles that are placed on the worktable of one of the processors. The processors remove leaves, cut flowers down to the right size, and finally create bunches that are labeled with the worker's ID number. Nearly all workers are observed in both positions (supplier and processor).

My primary data source is records of daily processor output from 2007 and 2008. There are 924 packing plant workers in total. The quantities produced were recorded on paper by the farm for remuneration purposes and subsequently converted to electronic format by the research team. A survey provides additional information about workers' experience, ethnicity, birthplace and other background information. Summary statistics are in table 1. 59 percent of workers are female and 46 percent Kikuyu. The average worker is 35 years old and has five years of tenure at the factory. These figures are similar for Kikuyu and Luo workers.

On average, workers are observed working for 22 days followed by two leave days. When a worker takes leave, another worker returning from leave joins the two remaining workers. Teams are observed for 10 consecutive days on average, but because there is substantial variation in the length of individual work spells, the same is true for team spells. The length of work spells is statistically unrelated to characteristics of workers and teams. 28280 different teams are observed during the sample period. Individual workers are observed on 90 different teams on average.

Suppliers are paid a piece rate w per rose finalized by the processors supplied throughout the sample period. In 2007, the first year of the sample period, each rose finalized by a processor earned her a piece rate 2w. Workers thus earn the same when working as a supplier and as a processor on average.⁴ In February 2008 the factory began paying the two processors based on their combined output, which led to a change in suppliers' incentives that I exploit in section 4.

2.3 Assignment to teams at the plant

Identification of the productivity effects of ethnic diversity is complicated by the fact that individuals typically sort into joint production, or are assigned to production units so as to maximize productivity. Any third factor that influences both a team's productivity and its ethnicity

⁴Workers were additionally paid a small fixed component.

configuration will induce spurious correlation between team output and diversity.

The plant I study is ideal for analyzing the impact of ethnic diversity on productivity because of its position rotation system. The supervisors described the system as follows. Workers returning from leave were assigned to open positions in the order in which they arrived at the plant in the morning. Supervisors would start in one corner of a packing hall and work their way through open positions row by row. A priori it is difficult to see how such an assignment system could lead to systematic correlation between the chacteristics of the workers in a team.

The team ethnicity configuration classification I use is depicted in figure 1b. With 46.10 percent Kikuyu and 53.90 percent Luo workers, 25.46 percent of teams should be ethnically homogeneous, 24.85 percent vertically mixed and 49.69 percent horizontally mixed, if assignment was random. The percentages observed in the data are 25.64/49.61/24.66 (p = 0.85) during the pre-conflict period, 27.38/48.35/24.26 (p = 0.44) during the conflict period and 25.32/49.26/25.42 (p = 0.68) during the team pay period.⁵ Appendix figure 1 displays the distribution of co-workers' tribe (and other characteristics) across Kikuyu and Luo suppliers, during each of the three periods. It is clear that workers are not assigned to, or sort into, teams based on ethnicity.

A possible concern is that the underlying (individual or joint) productivity of workers that end up in homogeneous teams may nevertheless differ from that of workers in diverse teams, for reasons unrelated to ethnicity itself. Suppose that individuals are equally productive in homogeneous and diverse teams but prefer interacting with coethnics, as in Becker (1957). In that case it may for example be that supervisors assign well-liked, high-productivity workers to desirable homogeneous teams. Appendix figure 2 displays the distribution of workers' gender, years of education and years of experience across homogeneous, horizontally mixed and vertically mixed teams, during each of the three sample periods. The distributions are essentially identical. A formal test of quasi-random assignment is in table 2. The matrices in the table display the characteristics, tribe \times gender \times past productivity, of one worker in the row dimension, and those of another worker in the team in the column dimension. The proportion of teams observed in a given cell is shown, as well as the proportion expected under the null hypothesis of independence between the row worker's characteristics and the column worker's characteristics. Because the worker rotation system leads to complex temporal correlation in team composition and output, the assumptions required for validity of Pearson's chi-square tests would be violated if all data was used. A periodical "snapshot" of data is thus used in the table: team compositions on the first day of every month.⁶ For the same reason, productivity is measured by a worker's average output in month t-2. The chi-square tests give no indication of systematic team assignment in any of the three sample periods.

In the context of the plant I study, quasi-random assignment is less surprising than one might

⁵The pre-conflict period is 2007. The conflict period is here considered the first six weeks of 2008, when processors were paid individually. The team pay period is the remainder of 2008 (see section 4).

⁶The tests are insignificant if data from other days is used instead. Note that the table uses three, binary worker characteristics in order to avoid small cell sizes and enable a visual presentation of the results. The Supplier - Processor 2 matrix is not displayed because the two processor positions are "interchangeable", but the chi-square statistics are insignificant also for that pair of workers.

think. Supervisors had little incentive to attempt to optimize team assignment,⁷ and little ability to do so given their limited knowledge of worker characteristics and the plant's leave and rotation system.⁸ Managers appeared to be unaware of systematic differences in output across teams of different ethnicity configurations during the first year of the sample period, their limited attention to the packing plant perhaps due to labor costs making up a relatively low proportion of flower farms' total costs (EDRI, 2008).

To alleviate any remaining concerns about systematic team assignment, individual fixed effects are used in the main regressions of the paper.

3. Discrimination: Theoretical Framework

3.1 Set-up

In the context of a joint production situation in Kenya in which workers perform standardized, repetitive tasks, it is reasonable to expect non-positive effects of ethnic diversity in teams. The simple, triangular structure of production at the plant also suggests that for example technological diversity effects - better communication in homogeneous teams, say - and informational diversity effects - e.g. downward-biased beliefs about non-coethnics' productivity - may have limited influence on output. Becker (1957) points out that the presence of other mechanisms is not necessary to explain potentially higher output in homogeneous production units if individuals have discriminatory tastes.

In this section, I present a simple framework in which the supply of intermediate flowers is skewed towards downstream workers of the supplier's ethnicity, and output thereby lowered, if suppliers have discriminatory preferences. The model's predictions are tested in the next section; in section 5 I consider the ability of non-taste-based ethnic diversity effects to explain the results.

Let production take place in teams consisting of one supplier and two processors, the supplier being paid w per rose produced by the team and each processor 2w per rose produced by the processor in question. Let processor output depend on supplier effort and ability, e_{sp} and α_s , and on processor effort and ability, e_p and α_p , through a concave output function displaying decreasing returns to scale, $q_p = f(e_{sp}, \alpha_s, e_p, \alpha_p)$. Worker *i*'s costs of production are given by an increasing and convex function of her total effort, $d(\sum e_i)$. Assume that the supplier and processors choose effort simultaneously.⁹ Finally, assume that the supplier attaches weight θ_p to the utility of processor p,

⁷Supervisors were rarely, if ever, promoted, and their pay did not depend on performance.

⁸Team rotation was unavoidable given the system of irregularly timed leave. The payroll department's representatives, who managed the leave system, explained that the system's flexibility reflected a demand from union representatives and management inertia. Having their families on-site and being able to take leave when needed apparently made infrequent leave acceptable to plant workers. Supervisors found out who was on duty on a given day as team assignment was taking place. An attempt at optimizing assignment by supervisors would thus (i) need to be accomplished in "real time", (ii) be constrained by the available workers returning from leave on a given day, and (iii) be further complicated by the fact that supervisors had limited knowledge of specific workers' characteristics. The reason is that management attempted to attract supervisors that were not socially connected to the rank and file, and low pay relative to the outside options of those considered qualified for supervisor jobs led to high turn-over.

⁹In reality, supply and processing decisions take place continuously throughout the work-day. A processor working fast relative to the supplier will at times be held up waiting for more roses, whereas the work-table of a processor working slowly will be overflowing with flowers. Early on, the supplier and processor likely react to each others' speeds; after a while an equilibrium work speed may be reached. When the time unit of the data to which the model

where θ_p can be either positive or negative.¹⁰ Suppliers with a different weight for coethnics and non-coethnics have discriminatory preferences.

A processor thus maximizes her utility of pay minus her cost of effort:

$$\operatorname{Max}_{e_{p}} 2wf(e_{sp}, \alpha_{s}, e_{p}, \alpha_{p}) - d(e_{p})$$

and the supplier her utility of pay minus her cost of effort plus the additional utility (or disutility) she derives from the well-being of processor 1 and processor 2:

$$\underset{e_{s1},e_{s2}}{\text{Max}} w \left(f \left(e_{s1}, \alpha_s, e_1, \alpha_1 \right) + f \left(e_{s2}, \alpha_s, e_2, \alpha_2 \right) \right) - d \left(e_{s1} + e_{s2} \right) \\ + \theta_1 \left(2wf \left(e_{s1}, \alpha_s, e_1, \alpha_1 \right) - d \left(e_1 \right) \right) + \theta_2 \left(2wf \left(e_{s2}, \alpha_s, e_2, \alpha_2 \right) - d \left(e_2 \right) \right)$$

If we abstract from the supplier's cost of effort for purposes of illustration, the analogy between the specification here and Becker (1957)'s specification of a taste for discrimination is clear. The supplier derives $w(1 + 2\theta_1)$ benefit from a unit of q_1 produced. If θ_1 is negative, the supplier is willing to pay out-of-pocket to lower the utility of processor 1. $2\theta_1 w$ is then effectively a Beckerstyle "discrimination coefficient". However, even if the supplier derives positive utility from ceteris paribus improvements in processor 1's well-being, she may be willing to accept lower own income in order to lower the income of processor 1 relative to processor 2 if $0 < \theta_1 < \theta_2$.

A full model with output a Cobb-Douglas function of its arguments is developed in the theoretical appendix, and the propositions it implies shown (proofs are in the online theoretical appendix). Here I lay out the intuition of the framework in the appendix and discuss its predictions for each of the three sample periods observed.

3.2 Pre-conflict period

Let $\theta_i = \theta_C$ if processor *i* is of the supplier's ethnic group, and $\theta_i = \theta_{NC}$ if not. Processors are then observed in four different positions: in homogeneous teams (*H*), in vertically mixed teams (*VM*), and in horizontally mixed teams in which the processor in question may (*HM*, *C*) or may not (*HM*, *NC*) be of the supplier's ethnic group. From a team perspective there are three types of ethnicity configurations, as illustrated in figure 1b. For conciseness, I do not distinguish between the two specific ethnic groups here; homogeneous teams may for example be either Kikuyu-Kikuyu-Kikuyu or Luo-Luo. When informative, I highlight the additional cases to be considered if ability or taste for discrimination differs across the two ethnic groups.

The model predicts that processor output is increasing in own ability and the ability of the supplier, but decreasing in the ability of the other processor, in equilibrium. A processor's output is also increasing in the weight the supplier attaches to her utility, but decreasing in the weight of the other processor. The reason is that the upstream worker, in making her supply decisions, considers not only her direct utility from pay, but also the indirect benefits she derive from the output of

must be compared is a whole work-day, the process of adjustment and re-adjustment to the speed(s) of the other worker(s) can sensibly be approximated by assuming simultaneous moves.

¹⁰This formulation follows Becker (1974), Charness and Rabin (2002) and others.

each of the two processors due to her weight on their utility. If the supplier has discriminatory preferences ($\theta_C > \theta_{NC}$), the model predicts that processor output is higher (a) when working with a coethnic supplier, and (b) when working with another processor who is not of the supplier's ethnicity: $q_{HM,C} > q_H > q_{VM} > q_{HM,NC}$.

Consider now the impact of upstream favoritism on total team output. Biased suppliers are predicted to discriminate both "horizontally" and "vertically" in mixed teams. Vertical discrimination occurs when an upstream worker undersupplies a processor of the other ethnic group - irrespective or her supply to the other processor in the team - because the returns to effort devoted to supplying non-coethnics are lower. Horizontal discrimination occurs when biased suppliers additionally "shift" roses from non-coethnic to coethnic processors, in which case the relative supply to the two processors deviates from that based on their relative productivities. Vertical and horizontal misallocation of roses is predicted to lower team output, so that output is higher homogeneous than in mixed teams: $Q_H > Q_{VM}$ and $Q_H > Q_{HM}$.¹¹

Total supply will be lower in vertically mixed teams than in horizontally mixed teams because the degree of vertical discrimination in teams is increasing in the number of non-coethnic downstream workers. But horizontal misallocation is predicted to occur only in horizontally mixed teams. The impact of horizontal misallocation on the average output of horizontally mixed teams will depend on (a) the ethnic make-up of the population of workers and (b) the relative productivity of individuals of different ethnic groups. If on average flowers are shifted towards comparatively unproductive workers when the two processors are of different ethnic groups, output in horizontally mixed teams may be lower than in vertically mixed teams. Otherwise output is expected to be lowest in vertically mixed teams.

The framework also predicts that a processor's output will benefit more from higher supplier ability (a) when working with a coethnic supplier, and (b) when working with another processor who is not of the supplier's ethnicity. The reason is that biased high-ability suppliers allocate more of their additional capacity to supplying coethnic processors. Thus: $\partial q_{HM,C}/\partial \alpha_s > \partial q_H/\partial \alpha_s >$ $\partial q_{VM}/\partial \alpha_s > \partial q_{HM,NC}/\partial \alpha_s$.

3.3 Conflict period

It is possible that the period of ethnic conflict in Kenya in early 2008 led to a change in attitudes towards co-workers of the other ethnic group, which I model as a change in θ_{NC} . If θ_{NC} falls, the output of the processor of the supplier's ethnicity in horizontally mixed teams is expected to increase - the relative benefits of supplying such processors go up in that case. A decrease in the output of non-coethnic processors is expected if θ_{NC} decreases. The fall in output will be greatest for non-coethnic processors in horizontally mixed teams because the *relative* benefits of supplying a non-coethnic processor also decrease when the other processor is of the supplier's ethnicity.

¹¹Note that horizontal misallocation occurs in this framework because the supplier's cost of effort function is convex in the sum of effort devoted to supplying the two processors. If instead the cost of effort devoted to one processor was separable from the cost of effort devoted to the other processor, horizontal misallocation would not occur. The assumption made here would appear more reasonable.

Unless conflict changes θ_C , output in homogeneous teams should be unaffected by conflict.¹² Thus, $\partial q_{HM,C}/\partial \theta_{NC} < 0 = q_H/\partial \theta_{NC} < \partial q_{VM}/\partial \theta_{NC} < \partial q_{HM,NC}/\partial \theta_{NC}$.

3.4 Team pay period

Six weeks into the conflict period the plant began paying processors for their combined output. Under such a pay system, processor 1's utility from pay is $w(q_1 + q_2)$, rather than $2wq_1$. Because a processor's pay thus partly depends on the effort of the other processor in the team, freeriding is expected, which will have a negative influence on output in all teams.

The supplier's pay system did not change, but due to her social preferences the supplier's problem changes and becomes:

$$\underset{e_{s1},e_{s2}}{\text{Max}} \quad w \left(f \left(e_{s1}, \alpha_s, e_1, \alpha_1 \right) + f \left(e_{s2}, \alpha_s, e_2, \alpha_2 \right) \right) - d \left(e_{s1} + e_{s2} \right) \\ + \left(\theta_1 + \theta_2 \right) w \left(f \left(e_{s1}, \alpha_s, e_1, \alpha_1 \right) + f \left(e_{s2}, \alpha_s, e_2, \alpha_2 \right) \right) - \theta_1 d \left(e_1 \right) - \theta_2 d \left(e_2 \right)$$

In scenarios in which the two downstream workers are of the same ethnic group - homogeneous and vertically mixed teams - the supplier's problem reduces to the same problem she faced under individual pay. In such teams, equilibrium production is thus expected to fall under team pay due to processor freeriding: $Q_H^{TP} < Q_H$ and $Q_{VM}^{TP} < Q_{VM}$.

Because the two processors in a team are paid the same under team pay, the supplier is unable to increase her own utility by "shifting" flowers from less to more favored processors. The average output of coethnic and non-coethnic processors in horizontally mixed teams is thus expected to be equal under team pay, even if suppliers have discriminatory preferences: $q_{HM,C}^{TP} = q_{HM,NC}^{TP}$. The impact of team pay on total output in horizontally mixed teams will depend on the relative magnitude of the positive effect of eliminating horizontal misallocation and the negative effect of processors freeriding on each other: $Q_{HM}^{TP} \ge Q_{HM}$.¹³

Because biased suppliers' incentive for vertical discrimination remains under team pay, output in homogeneous teams is expected to continue to exceed that in vertically mixed teams, if suppliers have discriminatory preferences: $Q_{H}^{TP} > Q_{VM}^{TP}$.

Figure 3 and table 3 summarize the predictions to be tested. The table also highlights where the predictions of non-taste-based models of ethnic diversity effects differ. In the next section I interpret the results in light of the model presented here; in section 5 I discuss the ability of non-taste-based mechanisms to explain the results.

4. The Effect of Ethnic Diversity on Productivity

4.1 Investigating the shape of the production function

 $^{^{12}}$ The results of Eifert et al. (2010) indicate that individuals' weight on coethnics' utility may increase during periods of ethnically-based political conflict. In that case, output in homogeneous teams is expected to increase in early 2008. Otherwise, no change in the output of homogeneous teams is expected.

¹³It is not the case in this framework that more is supplied to non-coethnic processors in horizontally mixed teams under team pay. This is because assuming simultaneous moves means that the supplier does not take processors' cost of effort into account when making her supply decisions.

The framework presented in the previous section predicts that processor output is increasing in processor and supplier ability, but decreasing in the ability of the other processor in the team. In order to correctly interpret observed ethnic diversity effects, it is useful to investigate the shape of the production function. Proxies for workers' ability as processor and as supplier are needed. I follow an approach comparable to that in Mas and Moretti (2009). Individual ability proxies are first estimated controlling for co-workers' identities. Focusing on homogeneous teams, processor p's output $q_{p,d}$ is regressed on indicator variables for processor p being worker i, supplier s worker k, and other processor o worker j, on date d:

$$q_{p,d} = \alpha_i^{p'} D_{i,d}^p + \beta'_j D_{j,d}^o + \alpha_k^{s'} D_{k,d}^s + \varepsilon_{p,d}$$

where $D_{i,d}^p = 1$ if p = i on date d. $D_{j,d}^o$ and $D_{k,d}^s$ are defined analogously. $\widehat{\alpha}_i^p$ then provides an estimate of i's "permanent productivity" as processor and $\widehat{\alpha}_i^s$ as supplier.¹⁴

Focusing on homogeneous teams during the first year of the sample period, figure 4 nonparametrically depicts how average processor output varies with (a) processor permanent productivity (across the x-axis), (b) supplier permanent productivity (across the plot lines), and (c) other processor permanent productivity (across panel A and B).¹⁵ As predicted by the model, processor output is increasing in processor and supplier productivity throughout the range. The reason why supplier productivity has a positive effect on output regardless of how slow the processor is (and vice versa) may for example be that tasks are not clearly separated. In that case a fast supplier can finish more of the work involved in packing a bunch of roses when working with a slow processor. Other processor's productivity appears to have a small but negative effect (unless the supplier is of low productivity) which indicates that upstream workers consider the benefits of supply to both downstream workers when making their supply decisions.

¹⁴Two limitations of this approach should be noted. (1) Ability proxies would ideally be estimated on, say, one half of the data, and then used in second-stage analysis using outcome data from the other half of the data. But the two-stage approach yields inconsistent and downward-biased estimates of the effect of one worker's ability on another worker's output in the second stage when T is fixed (Arcidiacono et al., 2011). This is likely unproblematic in Mas and Moretti (2009) because their data has a very large number of observations per worker over time, but the dataset used here, while also large, is significantly smaller than the one in Mas and Moretti (2009). Because a large T is important in two-stage approaches, I estimate the ability proxy using the whole period of data observed. (2) If the exact approach in Mas and Moretti (2009) was followed, $q_{p,d}$ would be regressed on $D_{i,d}^p$ and team dummies. However, in the current setting a team is defined as a specific worker in the supplier position and two other workers in the processor positions. The Mas and Moretti (2009) approach therefore provides no natural way to estimate supplier ability proxies (and only two processors share a given team dummy). I therefore use additive, individual fixed effects. Because it is not clear that additive fixed effects provide consistent estimates of structural ability parameters in a nonlinear production function, I simulate the model developed in the appendix in order to investigate how informative $\hat{\alpha}^p$ and $\hat{\alpha}^s$ are. The amount of output data used in the analysis is created using the model's expression for equilibrium $q_{p,d}$ and the empirical hazard rates for a worker leaving a team. Parameter values are chosen so as to approximate the observed mean and standard deviation of output. Estimating $\hat{\alpha}^p$ and $\hat{\alpha}^s$ on the simulated data using additive fixed effects then give correlations of 0.9 between $\hat{\alpha}^p$ and α^p and 0.75 between $\hat{\alpha}^s$ and α^s .

 $^{{}^{15}\}hat{\alpha}^p$ is normalized to have the mean and standard deviation of processor output, and $\hat{\alpha}^s$ the mean and standard deviation of team output. Note also that, because all suppliers in a packing hall obtain roses from the same "pool" of flowers arriving from the greenhouses, mechanically negative across-team "peer effects" should in theory be observed: less flowers are left for other teams if a given team is more productive. But such effects should be small for a sample of the size considered here, and other teams of different configurations should not be differentially affected.

4.2 Productivity in homogeneous and diverse teams: testing the predictions of the model in the pre-conflict, individual pay period

In the context of the plant, the productivity effect of ethnic diversity can be identified by comparing the output of teams of different ethnicity configurations. I begin by focusing on the first year of the sample period, when processors were paid based on own output, and before conflict began.

The histogram in figure 5 displays mean output by team ethnicity configuration in 2007, distinguishing between teams with Kikuyu and Luo suppliers. Confidence intervals are shown but are narrow. The magnitudes in the histogram are in the notes to the figure, along with the standard errors. Note first that there are no significant differences between teams with Kikuyu and Luo suppliers. Most importantly, all-Kikuyu teams are on average as productive as all-Luo teams. Given the nature of work at the plant, this is arguably unsurprising. Focusing instead on output differences that point to discriminatory behavior, it is also the case that the output gap between Kikuyu-Luo-Luo and all-Kikuyu teams is not significantly different from the output gap between Luo-Kikuyu-Kikuyu and all-Luo teams. The same is true for the gap in output between homogeneous and horizontally mixed teams. The evidence in figure 5 thus suggests that Kikuyu and Luo workers are of similar ability and equally discriminatory on average. These results enable a more concise presentation of the evidence to follow. In the remainder of the paper, I do not distinguish between specific ethnic groups and instead focus on the relation between the ethnic backgrounds of workers in a team.

It is clear in figure 5 that team output is highest in homogeneous teams and lowest in vertically mixed teams, with output in horizontally mixed teams falling in between the two. The distribution of team and processor output in teams of different ethnicity configurations is displayed in figure 6. Notably, the density of output for coethnic processors in horizontally mixed teams is shifted to the right of that in homogeneous teams. Conversely, the density of output for non-coethnic processors in horizontally mixed teams is shifted to the left of that in vertically mixed teams. The distributions appear close to normal.

Regression results corresponding to figure 5 are in table 4. The effects are very precisely estimated. Including individual fixed effects in the regressions has little influence on the results, as expected given quasi-random assignment to teams.¹⁶ The output of processors in vertically mixed teams is eight and a half percent lower than that of processors in homogeneous teams, an output gap that is also reflected in the total output of vertically mixed teams. As predicted by the model, upstream workers discriminate against non-coethnics downstream by undersupplying them, it appears. Such discrimination lowers final output.

The results in table 4 also indicate that suppliers discriminate horizontally. It is important to distinguish between the two processors in horizontally mixed teams. The output of the noncoethnic processor is eighteen percent lower than that of processors in homogeneous teams, and

¹⁶The average output associated with all types of teams is slightly higher when individual fixed effects are included, but the estimates of the output gap between teams of different configurations are essentially unaffected.

nine percent lower than that of processors in vertically mixed teams. The output of the coethnic processor is seven percent higher than that of processors in homogeneous teams. That processor output is lower if the other processor is of the same ethnicity as the supplier points to horizontal favoritism, as predicted by the model. As Becker (1957) emphasized, favored workers benefit from discrimination against non-favored workers. In some situations, such benefits may give favored individuals an incentive to maintain ethnic divisions in society.

Recall that the output loss from horizontal discrimination will depend on the relative productivity of favored and non-favored downstream workers. In the context of the farm, the two ethnic groups are similarly-sized, and we saw above that Kikuyu and Luo workers appear to be of similar ability on average. In such a situation, the output of vertically mixed teams is expected to be lower than that of horizontally mixed teams, which is what we see in table 4. Although vertically mixed are in aggregate four percent less productive than horizontally mixed teams, the lowest output processors are found in horizontally mixed teams. Even if the impact of horizontal discrimination on total output is limited when workers of different ethnic groups are of similar ability, the distribution of output across downstream workers is significantly affected.

Suppose, for purposes of illustration, that in the absence of misallocation of roses *across* the two processors in a team, the output of a coethnic processor in a horizontally mixed team would be equal to that of a processor in a homogeneous team. Similarly, suppose that in such a scenario the output of a non-coethnic processor in a horizontally mixed team would be equal to that of a processor in a vertically mixed team. In that case we can decompose the output gap between homogeneous and horizontally mixed teams: 14 percent would be due to the effect of horizontal misallocation and 86 percent due to vertical misallocation.¹⁷ While the magnitude of the "misallocation multiplier" associated with horizontal discrimination will depend on the relative productivity of those being favored and those being discriminated against, generally speaking intermediate goods note being passed downstream will tend to lower final output more than intermediate goods being "invested" in a less productive downstream producer.

The model also predicts that higher ability upstream workers will allocate more of their additional capacity to supplying downstream workers of their own ethnic group. In table 5, processor output is regressed on the proxy for supplier ability estimated above, interacted with team ethnicity configuration dummies. The results show that higher supplier productivity benefits noncoethnic processors less than coethnic processors, suggesting that $\partial q_{HM,C}/\partial \alpha_s > \partial q_{VM}/\partial \alpha_s >$ $\partial q_{HM,NC}/\partial \alpha_s$ and $\partial q_H/\partial \alpha_s > \partial q_{VM}/\partial \alpha_s > \partial q_{HM,NC}/\partial \alpha_s$. The effect of supplier ability is not significantly different for processors of the supplier's ethnic group in homogeneous and horizontally mixed teams.

In light of the model above, the results we have seen so far suggest that suppliers have discriminatory preferences. The output of a processor depends on her ethnic background in relation to that of the supplier, and on the ethnicity of the other processor in relation to that of the supplier. The

¹⁷This decomposition is subject to caveats in that it ignores the convexity of effort costs, and it is not clear that the effect of vertical and horizontal misallocation is "additive".

reason appears to be that upstream workers undersupply non-coethnics and distort their supply of intermediate flowers to benefit coethnics downstream. By doing so suppliers also lower their own pay. The results thus indicate that upstream workers are willing to pay to discriminate.¹⁸

The contrast between these findings and those of Bandiera et al. (2009) is noteworthy. The authors explore how "upstream" supervisors allocate their own effort and rows with different amounts of fruit across favored and non-favored "downstream" workers at a farm in the U.K. The setting in Bandiera et al. (2009) is thus comparable to the one studied here in terms of the tasks performed by upstream and downstream workers. The authors find that supervisors discriminate against downstream workers to whom they are not socially connected, but only when supervisors are paid fixed wages - that is, only when doing so is costless to the supervisor. It may thus be that ethnic antagonism is of greater importance to workers in Kenya than social (dis)connections are to workers in the U.K.

I now consider the extent to which explanations other than a negative output effect of ethnic diversity in teams may account for the results in table 4. The focus here is on documenting the causal impact of a team's ethnic composition on output; in section 5 I consider alternative theories that predict negative ethnic diversity effects but do so for reasons unrelated to discriminatory preferences.

The cleanest possible test for ethnic diversity effects in team production would switch the ethnicity of one worker in the team, holding constant everything else about that worker as well as the two other workers in the team. In table 6 I exploit the rotation system at the plant to provide arguably comparable evidence. The analysis explores what happens when a worker is replaced by another worker of the same productivity tercile but the other ethnicity, controlling for pair fixed effects for the pair of workers that remain in the team before and after the switch.¹⁹ Note that there is no significant change in output when the outgoing and incoming worker are of the same ethnic group: worker switches do not in themselves affect the productivity of a team.

In columns 1 and 3, the output of an *unswitched* processor is regressed on dummies for the change in team ethnicity configuration when a supplier or processor of productivity comparable to the replaced worker joins the team. For clarity, I lay out the effects for a worker in processor position 1 (processor 2 is analogous). The output of a processor 1 who is of the same ethnic group as the supplier increases by five percent when a processor 2 of the other ethnic group replaces a comparably productive processor 2 of the supplier's ethnic group. When a supplier who is not of processor 1's ethnic group replaces a comparably productive supplier of processor 1's ethnic group, processor 1's output falls by nine percent if the two processors are of the same ethnic group. If instead processor 2 is of the incoming supplier's ethnic group, processor 1's output falls by 25 percent. The output of a processor 1 who is not of the supplier's ethnic group increases by nine

 $^{^{18}}$ An alternative interpretation would be that the cost of effort devoted to supplying non-coethnic downstream workers is greater than that of supplying coethnic downstream workers. Such an interpretation provides a less satisfactory account of the observed occurrence of horizontal misallocation of flowers. The ability of theories of "technological" ethnic diversity effects to explain this paper's findings is discussed in section 5.

¹⁹The pair fixed effect for processor pair ij is for example a dummy that takes value 1 if workers i and j are processors in a team together.

percent if a processor 2 of processor 1's ethnic group replaces a comparably productive processor 2 of the supplier's ethnic group.

The estimates for team output in columns 3 and 4 are similar, output falling by five percent when a team goes from being homogeneous to horizontally mixed due to a worker switch, by nine percent when a team goes from being homogeneous to vertically mixed, and by four percent when a team goes from being horizontally to vertically mixed.

Comparing teams that share the workers in two positions and the productivity tercile of the worker in the third position thus yields similar estimates to comparing all teams of different ethnicity configurations, providing reassurance that the estimates in table 4 represent the causal effect of ethnic diversity. If the estimates in table 4 were due in part to for example non-random assignment to teams or differences in ability across the two ethnic groups interacting with non-linear complementarities in the production function, then controlling for pair fixed effects and the third worker's productivity tercile should lead to different estimates.

Figure 7 depicts the temporal response of team output to the "event" of a worker substitution leading to a change in a team's ethnicity configuration. Panels A - C plot the dynamic response of the first difference of output (the change in team output from the day before) to a change in a team's ethnicity configuration, and panels D - E the cumulative response over time. The decrease in output when a team "becomes mixed" is apparent. The first differenced response occurs almost entirely on the first day after the switch: the difference in output between homogeneous and diverse teams is relatively constant through teams' duration.

The tribal categorization used here is meaningful. Recall that this paper distinguishes primarily between workers designated as belonging to the Luo and Kikuyu tribal blocs. Categorization was on the basis of political alliances and relations between specific tribes. 86 percent of the sample belongs to three tribes: the Kikuyu (41 percent), Luo (30 percent) and Luhya (15 percent). I now consider sub-samples of teams in which workers belong to two specific tribes, focusing on the Kikuyu - Luo, Kikuyu - Luhya, and Luo - Luhya sub-samples. The Luo and Luhya tribes are categorized as belonging to the "Luo" ethnic group in this paper.

The estimates in table 7 provide a clear picture. In a sub-sample of teams consisting of workers from two different tribes categorized as belonging to the same tribal bloc, little if any discrimination against non-coethnic processors occurs. The output of vertically mixed teams is for example not significantly different from that of homogeneous teams in the Luo - Luhya sub-sample. But within two different sub-samples of teams consisting of workers of two specific tribes categorized as belonging to different tribal blocs here, discrimination is pervasive and of an extent similar to that seen in the full-sample analysis in table 4. There are only minor differences across the Kikuyu - Luo and the Kikuyu - Luhya sub-samples, analyzed in columns 1 - 2 and 3 - 4 of table 7 respectively.

So far we have seen strong evidence indicating that team-level ethnic diversity lowers productivity in the context of factory production in Kenya. If diversity effects are driven by discriminatory preferences, then we would expect the negative effect of ethnic diversity on private sector output to vary with factors that influence taste for discrimination, such as the political climate and relations between groups. A shift in taste for discrimination should differentially lower the output of mixed teams. In the next sub-section, I analyze differences in output between homogeneous and mixed teams during the period of ethnically-based, political conflict in Kenya in early 2008.

4.3 Ethnic conflict and the impact of diversity in teams on productivity: testing the predictions of the model in the conflict period

The two coalitions in Kenya's December 27 2007 presidential election were ethnically based. In advance of the election, opinion polls predicted that the coalition led by Luo challenger Raila Odinga would oust the sitting Kikuyu- led coalition represented by incumbent president Mwai Kibaki. But results were delayed and the Kibaki victory announced on December 29 disputed by the opposition and the international community. Widespread violence against Kikuyu and Kikuyuallied tribes erupted, and counter-attacks soon followed. More than 1,200 people were killed and 500,000 displaced in the months that followed (Gibson and Long, 2009). On February 28, a peace agreement was reached, though violence continued in many areas, and it was not until after April 3 when the two sides reached an agreement on the composition of a power-sharing government that the political crisis ebbed.

The conflict period significantly disrupted life in parts of Kenya.²⁰ However, plant supervisors reported that logistics and worker absence at the farm was largely unaffected and that production continued as usual. Because the workers live on the farm in a gated community it was safest to remain on the farm. If the plant's ability to operate was nevertheless affected, a decrease in productivity, as measured by the econometrician, should be observed in all teams.

The model predicts an increase in the gap between the average output of homogeneous and mixed teams if attitudes towards workers of the other ethnic group worsened when conflict began. I interpret a possible increase in taste for discrimination as a decrease in the weight attached to the well-being of non-coethnics.²¹

In table 8, the difference in output between mixed and homogeneous teams before and after conflict began is compared.²² Data from 2007 and the first six weeks of 2008 (when processors were still paid based on own output) is used.

There was no significant change in the output of homogeneous teams when conflict began. If suppliers have social preferences, the impact of conflict on the productivity of homogeneous teams will reflect a combination of (at least) two factors. First, farm-wide disruption effects may have negatively affected output in all teams. Second, it is possible that conflict led to an increase in workers'

 $^{^{20}}$ Dupas and Robinson (2010) document a dramatic fall in income and consumption for the rural poor in Western Kenya during the crisis. Many flower farms also struggled: Ksoll et al. (2010) report that the official export volumes of affected farms dropped by 38 percent on average, in large part due to worker absence exceeding 50 percent on average on such farms.

 $^{^{21}}$ Eifert et al. (2010) show that ethnic identities can vary over time, and Charness and Rabin (2002) and others show that social preferences generally depend on the behavior of others. As long as social preference weights are partly group-based rather than entirely individual-specific, we would then expect the weight on non-coethnic co-workers' output and utility to deteriorate during a period of increased antagonism.

²²Data from both 2007 and 2008 was de-seasonalized as follows. Let m_i be average output in month *i* of 2007, and $\overline{m} = \frac{1}{12} \sum m_i$. Output observations from month *i* of both 2007 and 2008 were then multiplied by \overline{m}/m_i .

weight on the utility of coethnics: the findings of Eifert et al. (2010) suggest that Africans increasingly identify with coethnics during times of heightened political competition between groups. I cannot rule out general disruption effects or an increase in the utility workers derive from coethnics' output and income. But the combination of supervisors' reports and a conflict coefficient for homogeneous teams that is essentially precisely zero points to little farm-wide disruption effects and little effect on workers' weight on coethnics' utility.

The output gap between homogeneous and vertically mixed teams nearly doubled in early 2008. Output in vertically mixed teams decreased by seven percent when conflict began. The results in table 8 thus indicate that upstream workers undersupply non-coethnic downstream workers to a significantly greater extent during times of ethnic conflict, as predicted by the model if taste for discrimination increased.

Output in horizontally mixed teams decreased by four percent when conflict began, but there was a small but significant *increase* in the output of coethnic processors in horizontally mixed teams. An increase in upstream discrimination against workers of other ethnic groups thus appears to increase the supply of flowers to those downstream workers who belong to the same ethnic group as suppliers, as predicted by the model. The relative benefits of flowers supplied to coethnic processors in horizontally mixed teams go up if conflict lowers the utility upstream workers derive from non-coethnics' output, even if suppliers' weight on coethnics' utility is unaffected.

In light of the model presented above, the results for the conflict period thus suggest that discriminatory attitudes towards co-workers of other ethnic groups worsened in Kenya in early 2008. It appears that the economic costs of ethnic diversity vary with the political environment. A back-of-the-envelope calculation suggests that the increase in supplier discrimination during conflict may have cost the farm as much as US\$560,000 in profit per year, had it not responded.²³

Firms may be forced to take measures to limit distortions that arise from internal, ethnic discrimination, especially in times of conflict. In the next sub- section, I analyze how the gap in output between homogeneous and mixed teams was affected when the plant six weeks into the conflict period changed the pay system for processors and thereby altered the incentives facted by biased upstream workers.

4.4 Firms' response to distortionary favoritism and the impact of diversity in teams on productivity: testing the predictions of the model in the team pay period

On February 11 2008, the farm began paying processors w per rose finalized by the team, rather than 2w per rose finalized by the processor herself as before. As in standard incentive models, the framework above predicts that processors will freeride on each others' effort when paid in part based on the output of the other processor. Freeriding should negatively affect output in all teams, but in horizontally mixed teams an offsetting positive effect is expected. Under team pay, suppliers are unable to influence the relative pay of the two processors through relative supply. If the higher

 $^{^{23}}$ US\$560,000 \approx 286 (average number of teams observed per day) \times 233 (average number of fewer roses produced per team per day during the conflict period, relative to 2007) \times 365 production days per year \times 0.023 \times (estimated average profit per rose grown in Kenya as estimated in Melese and Helmsing (2010)).

output for processors of the supplier's ethnic group observed under individual pay is driven by suppliers' taste for discrimination, a decrease in the output gap between coethnic and non-coethnic processors in horizontally mixed teams is thus expected when team pay is introduced.

To test these predictions, I consider the period after processors' pay system was changed and through the remainder of 2008 as a single team pay period.²⁴ Figure 8 displays team and individual output during the three sample periods: pre-conflict (2007), conflict (the first six weeks of 2008), and the team pay period (February 11 through 2008). The decrease in output in mixed teams during conflict is apparent. Comparing the second and third periods, the figure also clearly indicates that the introduction of team pay had a positive effect on output in horizontally mixed teams.

Corresponding regression results are in table 9. The results indicate that team pay leads to some degree of freeriding among processors: output in homogeneous and vertically mixed teams is 1 percent lower under team pay. The modest magnitude of this effect is noteworthy and interesting in itself.²⁵

Output in horizontally mixed teams is four percent higher under team pay, as seen in columns 3-4 and 7-8 in table 9. The difference in output between horizontally mixed and homogeneous teams thus decreased significantly when team pay was introduced. The introduction of team pay essentially canceled out the effect of conflict on output in horizontally mixed teams, returning the difference in output between homogeneous and horizontally mixed teams to pre-conflict levels.

The increase in horizontally mixed teams' output appears to be due to horizontal favoritism being eliminated when biased suppliers' ability to increase the relative income of favored processors through relative supply was removed, as predicted by the model. There is no statistically significant difference in the output of the coethnic processor and the non-coethnic processor in horizontally mixed teams during the last ten and a half months of 2008. An output gap of 32 percent between processors of the supplier's ethnicity and processors who are not of the supplier's ethnicity in horizontally mixed teams was eliminated by the introduction of team pay.

The positive impact on output in horizontally mixed teams, which make up half of all teams, led to an overall increase in output when team pay was introduced. However, output in horizontally mixed teams remains lower than in homogeneous teams under team pay, and output in vertically mixed teams still lower. Under team pay a biased supplier continues to derive greater benefit from flowers supplied the more downstream workers belong to her tribe. The ranking of output of teams of different ethnicity configurations observed under team pay is thus due to incentives for vertical discrimination remaining in place, it appears.

The model presented above, in which the productivity effect of ethnic diversity in teams arises

 $^{^{24}}$ In principle, we could distinguish between a "team pay / conflict" period and a "team pay / post-conflict" period. But it is unclear exactly when conflict effectively ended, and, as discussed below, differences in output between teams of difference ethnicity configurations remained essentially constant after team pay was introduced.

²⁵As is clear from figure 1, processors can easily monitor each others' effort. A triangular organization of production may thus be a situation in which freeriding can be effectively dampened through co-monitoring. Note that I cannot rule out that other differences between the individual and team pay periods of 2008 contribute to the team pay coefficient for homogeneous and vertically mixed teams. Such time-varying factors should not influence the comparison of different types of teams.

from a taste for discrimination on the part of upstream workers, thus predicts the output response to the introduction of team pay well. Approximately one fourth of the yearly expected profit loss due to the impact of conflict on misallocation of flowers (had the farm not responded) was avoided through the change in suppliers' contractual incentives.²⁶ It is difficult to imagine a standard economic model of joint production that would predict an increase in output when team pay is introduced.

In the previous sub-section we saw that the economic costs of ethnic diversity vary with the political environment. The reason appears to be that distortionary discrimination at work increases during times of conflict. The results in this sub-section suggest that, in high-cost environments, firms adopt "second best" policies to limit the distortions caused by ethnic favoritism. Group-based pay leads to freeriding and reduces output in homogeneous teams, but the new pay system introduced by the plant during the conflict period in Kenya in early 2008 was likely designed to remove the ability of biased upstream workers to increase one processor's pay relative to the other's through differential allocation of flowers. Distortionary discrimination fell and the net effect was positive. Interestingly, LaFerrara (2002) also finds that ethnically diverse cooperatives in Nairobi are more likely to adopt group-pay. It thus appears that ethnic diversity has an important influence on how firms organize production in the private sector.

In the next section I discuss the ability of non-taste-based ethnic diversity effects to explain the results we have seen so far.

5. Sources of Ethnic Diversity Effects

Taste-based discrimination is only one of many potential reasons why output may be lower in diverse teams than in homogeneous teams. Distinguishing between different sources of diversity effects is important. Unlike if differential allocation of intermediate goods to coethnic and non-coethnic downstream workers is driven by discrimination, higher supply to coethnic downstream workers may for example be *efficient* if individuals are simply more productive when collaborating with others of their own ethnic group.

The sources of non-taste-based, negative ethnic diversity effects discussed in the literature can be classified into three broad categories:²⁷

1. Informational diversity effects arise if upstream workers are risk-averse and better able to judge the productivity of coethnics, or have downward-biased beliefs about the productivity of non-coethnics (Becker, 1957). Such informational effects will lead to higher supply to downstream coethnics. Note that, in the context of the sample plant, a supplier who supplies "too few" roses to a non-coethnic processor may never learn the processor's true productivity.

²⁶Note that after the conflict period the plant also hired more plant workers, probably to make up for lost capacity due to the decrease in productivity. Though workers are paid piece rates, overhead costs per worker are significant (housing, etc). The actual change in profit when conflict began, and after team pay was introduced, is thus difficult to estimate. Workers that were hired after conflict began are excluded from the analysis in this paper.

 $^{^{27}}$ Habyarimana et al. (2007) uses a similar classification, but their focus is on explaining why public goods provision is lower in diverse societies.

- Technological diversity effects arise if individual productivity is higher when working with coethnics, for example due to better communication or peer effects among coethnics (Lang, 1986). All workers in the sample speak Swahili, but complicated forms of peer effects could explain the results in table 4.²⁸
- 3. "Cooperational" diversity effects arise if coethnics are better able to sustain cooperation (Kandel and Lazear, 1992; Habyarimana et al., 2007). Coordinating on a high effort equilibrium is more easily achieved if deviators can be effectively sanctioned. If workers of different ethnic groups segregate socially, it may be easier to punish deviators within an ethnic community.

I consider these possibilities in turn. Note first that informational and technological diversity effects are unlikely to explain this paper's results. Suppose that the higher output observed in homogeneous teams during the pre-conflict, individual pay period was due to inferior technology or information in diverse teams. In that case it is difficult to see why output in mixed teams would fall differentially during conflict, and why the output of the two processors in horizontally mixed teams would be equalized under team pay.

Cooperational effects have proven difficult to distinguish from social preferences (see for example Bandiera et al., 2005), in part because such theories typically have few testable implications. Some forms of cooperational diversity effects could explain the observed decrease in mixed teams' output during conflict. If trust for example facilitates cooperation, an erosion of trust between workers of different ethnic groups during times of ethnic antagonism could lead to a decrease in mixed teams' output. Other forms of cooperational diversity effects could explain the observed increase in the output of non-coethnic processors in horizontally mixed teams under team pay. Coethnic processors that can exert effective social pressure on the upstream worker may for example induce the supplier to supply more to non-coethnic processors in horizontally mixed teams under team pay because processors derive benefits from the output of the other processor under team pay. It is, however, difficult to think of cooperational or other forms of non-taste-based ethnic diversity effects that can simultaneously explain a decrease in mixed teams' output during conflict, equalization of processors' output in horizontally mixed teams when team pay is introduced, and the other results seen in this paper.

Though I cannot rule out that other forms of ethnic diversity effects also play a role, I thus conclude that the leading explanation for the lower output observed in ethnically diverse teams at the plant is taste-based discrimination on the part of suppliers.²⁹

So far we have seen that output in factory production in Kenya is lower when individuals of different ethnic backgrounds work together, and that the reason appears to be that biased upstream workers undersupply downstream workers of other ethnic groups and misallocate intermediate goods

²⁸In particular, non-linear, ethnicity-specific, positive peer effects could explain the results in table 4. Suppose that workers' effort responds to co-workers' effort but only that of coethnics. Suppose further that, within ethnic groups, working with highly productive co-workers increases effort but working with less productive workers does not decrease effort. In that case, homogeneous teams will be more productive than mixed teams.

²⁹More complicated forms of social preferences than the simple differential weight attached to coethnics' and noncoethnics' well-being in the model above may also explain this paper's results.

across coethnic and non-coethnic downstream workers. We have also seen that distortionary workplace discrimination is greater durings times of conflict, and that firms introduce policies in response in order to reduce workers' incentive to discriminate. By studying how discriminatory preferences are shaped, and how firms choose their response to distortionary discrimination, researchers can go beyond identifying a source of ethnic diversity effects in production and begin to address why those effects vary across space and time and how profit motives in the private sector can reduce the aggregate effect of ethnic diversity. I address these questions in more depth in the next two sections.

6. Understanding the Response of Workplace Behavior to Conflict

6.1 Magnitude of the increase in taste for discrimination

In this section I explore the magnitude, persistence, and heterogeneity of the response of individuals' taste for discrimination to conflict between groups.

By how much did suppliers' weight on the utility of non-coethnics fall when conflict began? A limitation of studying triangular production units is that I am unable to separately identify the structural parameters θ_C and θ_{NC} because suppliers are never observed working purely for their own benefit. But by taking advantage of the plant's worker rotation system I can bound the impact of conflict on θ_{NC} though a reduced form approach along the lines advocated by Chetty (2009). The required assumption is that θ_C was unaffected by conflict, an assumption supported by the fact that average output in homogeneous teams did not change during the conflict period.

Step 1: Ratios. In the Cobb-Douglas model developed in the theoretical appendix, the ability of the supplier does not influence the relative output of the two processors:

$$\frac{q_1}{q_2} = \left(\frac{\alpha_1}{\alpha_2}\right)^{\frac{2\beta}{2-\beta-2\gamma}} \left(\frac{1+2\theta_1}{1+2\theta_2}\right)^{\frac{2\gamma}{2-\beta-2\gamma}}$$

Step 2: Ratio-of-ratios. Recall that two workers in a team stay put when the third worker is switched for another worker returning from leave. Consider a sample of horizontally mixed teams in which a supplier of processor 1's ethnicity is replaced by a supplier of processor 2's ethnicity (say in between dates d = 0 and d = 1). In the model in the appendix, the relative ability of the two processors does not influence their relative output under one supplier relative to their relative output under another supplier:

$$\frac{q_{1,d=0}/q_{2,d=0}}{q_{1,d=1}/q_{2,d=1}} = \left(\frac{1+2\theta_C}{1+2\theta_{NC}}\right)^{\frac{4\gamma}{2-\beta-2\gamma}}$$

Taking the ratio of the ratio of processors' output before a supplier switch to the same ratio after the switch can be thought of as the multiplicative model analogue of a difference-in-differences analysis in additive models. We are left with a quantity that depends only on the powers of the output function, θ_C and θ_{NC} . Step 3: Ratio-of-ratio-of-ratios. Finally, if θ_C was unaffected by conflict, suppliers' weight on coethnics' utility should have the same influence on the ratio-of-ratios before and after conflict. Taking the ratio of the pre- and during-conflict quantities, we arrive at an expression that relates θ'_{NC} , the weight on non-coethnics' utility after conflict began, to the pre-conflict θ_{NC} :

$$\frac{\left(q_{1,d=0}/q_{2,d=0}\right)/\left(q_{1,d=1}/q_{2,d=1}\right)}{\left(q_{1,d=0'}/q_{2,d=0'}\right)/\left(q_{1,d=1'}/q_{2,d=1'}\right)} = \left(\frac{1+2\theta_{NC}}{1+2\theta'_{NC}}\right)^{\frac{4\gamma}{2-\beta-2\gamma}}$$

In the empirical appendix I implement the ratios approach. I bound $\Delta \theta_{NC} = (\theta_{NC} - \theta'_{NC})$ by considering a wide range of possible values for θ_{NC} , β and γ . I estimate a fall in θ_{NC} of 0.01 - 0.07 or 8 - 127 percent. Averaging across the parameter space considered, θ_{NC} is estimated to fall by approximately 35 percent when conflict begins.

This calculation is subject to caveats, but it illustrates an important point. If the decrease in mixed teams' output when conflict began was primarily due to a worsening of discriminatory attitudes, as the results in the previous sections suggest, then production data points to a relatively large increase in taste for discrimination against co-workers of the rival tribe in Kenya in early 2008.

6.2 Persistence of the effect of conflict on workplace discrimination

The effect of conflict on discriminatory workplace behavior does not decay in the nine months after conflict ended. In the model of taste-based discrimination above, the impact of conflict on output in diverse teams should persist for as long as attitudes towards workers of other ethnic groups are affected. Periods of increased antagonism may entail significant hidden economic costs if "mean reversion" in taste for discrimination is slow (or does not occur). The evolution of output in teams of different ethnicity configurations across the three sample periods was depicted in figure 2. After the introduction of team pay, average output in both homogeneous and mixed teams was steady for the remainder of the sample period, suggesting that the impact of conflict on social preferences was long-lived.

6.3 Heterogeneity in workers' response to conflict

How did the response to conflict of distortionary discrimination at work vary across individuals? Modeling θ_C and θ_{NC} as parameter values shared by all workers is a simplification: in reality some workers will have a higher taste for discrimination than others. Figure 9 plots the distribution, across individual suppliers, of the difference in output between homogeneous and (vertically and horizontally) mixed teams supplied, before and after conflict began. It appears that most suppliers discriminate against non-coethnic processors during the pre-conflict period. Conflict led to an increase in the output gap between homogeneous and mixed teams supplied for most upstream workers, but also to a notable widening of the distribution of the output gap. The figure indicates that some upstream workers respond more to conflict than others, differentially increasing the extent to which they discriminate against non-coethnics downstream.

Some workers in the sample were more exposed to the conflict period of early 2008 than others. Though the workers at the plant and their co-habitating family-members were not themselves directly affected, 22 percent of workers report to have "lost a relative" during the conflict.³⁰ The decrease in output in mixed teams when conflict began was significantly greater in teams supplied by such workers, as seen in columns 1 and 2 of table 10. These results indicate that personal grievances exacerbate individuals' workplace response to conflict.³¹

Younger individuals may have more malleable social preferences. In columns 3 and 4 of table 10 we see that, although output in homogeneous teams led by old and young suppliers was similar, output in mixed teams with young suppliers was significantly higher during the first year of the sample period. Young suppliers were less discriminatory towards non-coethnic co-workers than old suppliers before conflict began, it appears. This finding is consistent with an expectation expressed by many Kenya commentators before 2008. It was argued that the young coming of age at the time would be the country's first "post-tribal" generation (Washington Post, 1997). The results of table 10 also show that the decrease in output in mixed teams when conflict began was significantly greater in teams with young suppliers, however. Output in mixed teams with young suppliers was no higher than in mixed teams with older suppliers during the conflict period. These results suggest that youth start out relatively tolerant, but that the attitudes of the young towards non-coethnics respond more negatively to conflict.

The results discussed in this section paint a consistent picture of how distortionary attitudes towards workers of other ethnic groups respond to ethnic conflict. It appears that conflict may entail significant hidden economic costs because distortionary social preferences are updated in a "Bayesian" fashion when conflict occurs, at least in the Kenyan context. A serious episode of violent, political conflict between the Kikuyu and Luo blocs led to a significant shift in the average weight attached to the well-being of non-coethnics, a shift that did not decay in the nine months after conflict ended. The negative response was greater among those more affected and among those likely to have a less cemented "prior".

In the next section I analyze how the plant responded to lower output in mixed teams in more depth.

7. Understanding Firms' Response to Ethnic Diversity Distortions

7.1 Benefits of ethnicity-based assignment to teams

Segregating workers of different ethnic groups would appear to be the profit-maximizing response to distortionary discrimination, from the viewpoint of the econometrician. The results in tables 4 and 8 suggest that segregation would have increased plant productivity by four percent before conflict and by eight percent after conflict began, relative to the status quo of arbitrary assignment to teams. Are these expected benefits of a magnitude that is likely to be salient to supervisors? Consider the output increase expected from optimally assigning workers to teams and positions

³⁰Note that the high proportion of workers reporting to have a lost relative implies a broad definition of "relative". ³¹In ongoing work I am analyzing the response of discrimination and productivity to specific conflict events through

an event study comparing workers' behavior on days in which events occurred in their "home district" (where their relatives reside) to other days. I am also exploring how the response of discrimination to conflict events depends on the ethnicity configuration of the supplier's team on an event day in relation to the "configuration" of the event itself. Krueger and Mas (2004) find that a labor dispute in Illinois had a greater impact on employees' workplace behavior when replacement workers and returning strikers worked side by side.

based on ethnicity, productivity or both. If we view a worker as having three characteristics - the tercile to which she belongs in the distribution of processor productivity, the tercile to which she belongs in the distribution of supplier productivity, and her ethnicity - then an average output will be associated with teams of each of 3 ethnicity configurations, 18 productivity configurations and 63 ethnicity-productivity configurations.³² In theory, supervisors can then solve the linear programming problem of maximizing total output subject to the expected output associated with a given type of team and the "budget set" of workers available (see Bhattacharya, 2009; Graham et al., 2011).³³

The optimal assignments and associated expected output gains are shown in table 11.³⁴ Throughout the period observed, the output gains expected from assigning workers to teams based on ethnicity were larger than those expected from assigning workers based on productivity - twice as large during the conflict period. In fact segregation achieves about half the output gains of the "complete" solution. The complete solution assigns workers optimally to fully specified teams and thus takes into account interactions between the three workers' ethnicities and productivities - a complicated "general equilibrium" problem that is likely infeasible for supervisors to solve.³⁵ It thus appears that the expected productivity gain of segregation is sizable relative to the expected effect of changing other comparable factors under supervisors' control.

7.2 Costs of ethnicity-based assignment to teams

The fact that the plant chose not segregate workers, even after conflict led to a dramatic drop in productivity in mixed teams, indicates that managers expect there to be costs associated with segregation. I consider two specific possibilities. First, it may be that interacting with co-workers of other ethnic groups in itself dampens discriminatory attitudes over time. Second, the expected benefits of segregation computed in table 11 may not give an accurate picture of the "out-of-sample" possibility of plant-wide segregation.

Boisjoly et al. (2006) find that white American college students become more friendly towards and supportive of African American students after spending time with a black roommate. It is possible that a similar effect occurs in a Kenyan workplace, although in a situation in which mixed teams are characterized by discriminatory behavior it is also possible that interaction increases tensions and exacerbates ethnic biases. To investigate, I compare the behavior of suppliers with

 $^{^{32}63 = [3 * ((3 * (3 + 1))/2)] + 3^3 + [3 * ((3 * (3 + 1))/2)]}$. In teams in which the two processors are of the same ethnic group, the processors (i.e., the productivity terciles of the processors) are "interchangeable" so there are [3 * ((3 * (3 + 1))/2)] homogeneous types of teams and [3 * ((3 * (3 + 1))/2)] vertically mixed types of teams. In horizontally mixed teams, the processors' productivity terciles are not interchangeable because the higher ability processor may or may not be of the supplier's ethnic group, so there are 3^3 types of horizontally mixed teams.

³³Bhattacharya and Dupas (2011, forthcoming) and Carrell et al. (2011) compute welfare-maximizing assignments in other contexts using this technique. An added complexity here is the need to assign workers to both positions and teams.

 $^{^{34}}$ "Optimal" here means output-maximizing, as infered from the data. The output-maximizing solution may be undesirable for other reasons discussed below.

³⁵An example of a fully specified team is the following: {(Worker in processor position 1: 1st productivity tercile as processor, 3rd productivity tercile as supplier, Kikuyu), (Worker in processor position 2: 2nd productivity tercile as processor, 3rd productivity tercile as supplier, Luo), (Worker in supplier position: 1st productivity tercile as processor, 1st productivity tercile as supplier, Kikuyu)}.

greater versus lower experience working with non-coethnics, in table 12. Focusing on output during the second half of 2007 and the first six weeks of 2008, I contrast teams with suppliers with aboveaverage versus below-average time spent in mixed teams during the first half of 2007. Because most workers at the farm had already spent significant time working with non-coethnics before 2007, columns 3 and 4 restrict the sample to those with below-average tenure. The results show no significant effect of time spent working with non-coethnics on the output gap between mixed and homogeneous teams supplied, neither before nor after conflict began. Workers who have interacted more with individuals of other ethnic groups thus appear no less discriminatory in production.

The results in table 12 do not rule out the possibility that complete segregation between the two ethnic groups over time would have a negative influence on attitudes or behavior towards noncoethnics, however. Carrell et al. (2011) find that implementing an estimated optimal assignment can have unintended consequences due to unforeseen responses on the part of individuals to out-ofsample assignments. In the context of the sample farm, in a country that has experienced periodical violent clashes between ethnic groups, and where workers of different ethnic groups reside in the same quarters, complete segregation at the plant could for example lead to increased social tensions on the farm.

7.3 Firm's response to distortions due to ethnic diversity

Nevertheless, it is arguably surprising that a supposedly profit-maximizing firm chose to leave large productivity gains "on the table" by not segregating workers of different ethnicities. Ethical considerations add complexity to the issue of team assignment in Kenya, but we would perhaps expect longer-term costs of segregation to be incurred primarily by society, rather than the firm itself, in which case a case can be made for government intervention to enforce integration within firms.

Becker (1957) pointed out that discriminatory employers should go out of business as their profits suffer. A priori, the same argument should hold for flower farms that allow workplace discrimination to influence productivity. However, the floriculture business is not particularly competitive, as evidenced by high profit margins (African Business, 2011).³⁶ Moreover, as the literature in macroeconomics on across-firm misallocation has highlighted, it is not necessarily the most productive firms that survive in poor countries' economies (Banerjee and Moll, forthcoming; Hsieh and Klenow, 2009).³⁷

Further, plant managers *did* respond to the increase in distortionary discrimination when conflict began, as we have seen. The introduction of team pay for processors was likely motivated by the decrease in productivity in diverse teams in early 2008. It is unsurprising that the dramatic differential decrease in mixed teams' output when conflict began led managers to respond, even though the lower output observed in diverse teams during the first year of the sample period did

³⁶Entry- and exit- barriers are significant: large areas of land and expensive, complicated equipment is needed to produce roses and other cut flowers.

³⁷And even national chain stores in the U.S. with access to large amounts of electronic data and analysis appear to forego profit by not assigning workers to teams optimally (Mas and Moretti, 2009).

not. A doubling of the output gap of diverse teams during a short period of time is likely more salient to managers than potential foregone productivity gains from arbitrary assignment to teams.

It appears that managers considered an adjustment to contractual incentives a more desirable response to distortionary discrimination than segregating workers. But note that it is likely not possible to eliminate discrimination through contractual incentives, without entirely breaking the link between workers' output and pay. At the sample plant, vertical discrimination continued to significantly affect output after the introduction of team pay.

8. Conclusion

Evidence suggests that ethnic diversity negatively affects public goods provision and the quality of macroeconomic policies. While the possibility of an additional, direct effect on micro-level productivity has long been recognized, corresponding evidence is largely absent. In this paper, I begin by identifying a sizable, negative productivity effect of ethnic diversity in teams in Kenya. I do so using two years of daily output data for 924 workers, almost equally drawn from two rival tribes, at a flower-packing plant. The packing process takes place in triangular production units, one upstream "supplier" supplying two downstream "processors" who finalize bunches of flowers. I show that an arbitrary position rotation system led to quasi-random variation in teams' ethnicity configuration. As predicted by a model in which different weight is attached to coethnic and noncoethnic downstream workers' utility, suppliers discriminate both "vertically" - undersupplying downstream non-coethnics - and "horizontally" - shifting flowers from non-coethnic to coethnics downstream workers. By doing so, upstream workers lower their own pay and total output.

I show that less distortionary, non-taste-based ethnic diversity effects are unlikely to explain this paper's results. As Becker points out, significant aggregate effects "could easily result from the manner in which individual tastes for discrimination allocate resources within a free-enterprise framework" (Becker, 1957, p. 30). Discrimination should lead to misallocation of resources in most joint production situations in which individuals influence the output and income of others. I take advantage of two natural experiments during the time period observed to begin to explore how the productivity effects of ethnic diversity are likely to vary across time and space. When contentious presidential election results led to political conflict and violent clashes between the two ethnic groups represented in the sample in early 2008, a dramatic, differential decrease in the output of mixed teams followed, as predicted by the model. The reason appears to be that workers' taste for discrimination against non-coethnic co-workers increased. I estimate a decrease in the weight attached to non-coethnics' utility of approximately 35 percent in early 2008, through a reduced form approach. A back-of-the-envelope calculation suggests that the increase in distortionary workplace discrimination may have cost the plant half a million dollars in annual profit, had it not responded.

Six weeks into the conflict period, the plant implemented a new pay system in which downstream workers were paid for their combined output ("team pay"). Under team pay, biased upstream workers are unable to increase the relative pay of favored downstream workers by distorting relative supply. As a result, horizontal misallocation of flowers was eliminated. Total output in teams in which the two processors were of different ethnic groups therefore increased, the introduction of team pay returning the difference in output between such teams and homogeneous teams to preconflict levels. Overall output also increased, even though the results indicate that team pay led processors to freeride on each others' effort.

This paper's results indicate that, if taste for discrimination is high enough, firms are forced to adopt "second best" policies to limit the distortions caused by such discrimination. But entirely removing workers' incentives for discrimination is difficult. At the plant, team pay had little effect on the degree of discrimination in teams that were ethnically differentiated vertically rather than horizontally, as also predicted by the model. The obvious "solution" to discrimination - segregating workers - may be undesirable for reasons unrelated to productivity in the short term. The extent and multiplier effects of taste-based misallocation also depend on a number of other factors, such as pay systems, the structure of production, and the "geographical" distribution of ethnic groups in the productive system, however. More speculatively, it is possible that such factors respond endogenously to ethnic diversity. Social segregation is commonly observed in diverse societies but likely becomes harder to achieve as urbanization brings larger groups of workers together. The linkages and specialization required in industrialized production are rarely observed in the most ethnically diverse countries.

My findings also suggest that the economic costs of ethnic diversity vary with the political environment. Relatively brief episodes of ethnic conflict can have a long-lasting impact on economically distortionary attitudes: I find no decay in discrimination in the nine months after conflict ended. Multiple equilibria may thus exist if the occurrence of conflict itself depends on attitudes towards non-coethnics, some diverse societies being characterized by tolerance and little conflict and others by ethnic biases and frequent conflict.

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Figures

Figure 1a: Organization of team production

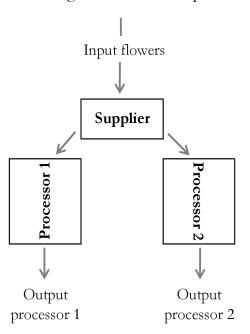
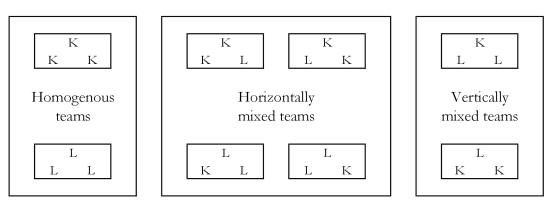


Figure 1b: Team ethnicity configuration categories



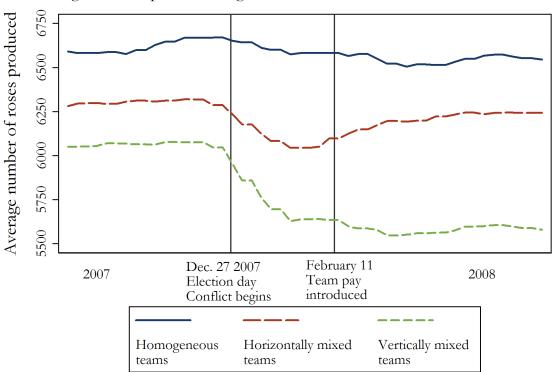
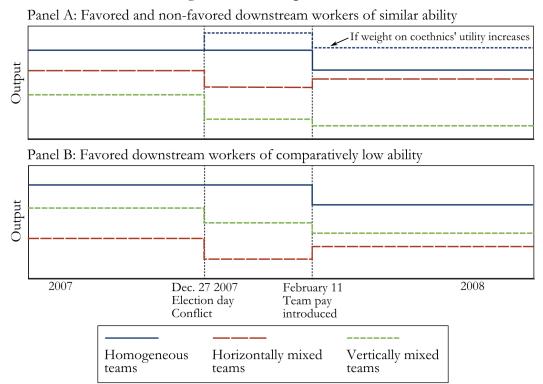


Figure 2: Output in homogeneous and mixed teams across time

Figure 3: Model predictions



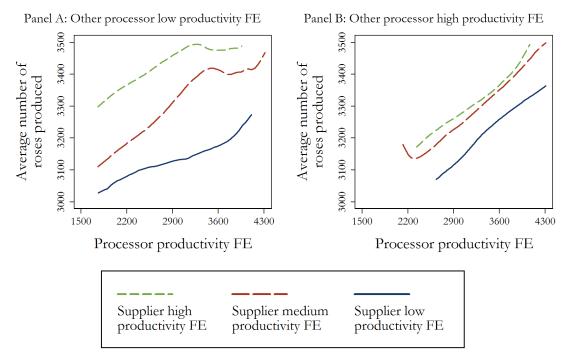


Figure 4: Investigating the shape of the production function

Data from 2007. Outliers (top and bottom percentile) excluded. Local polynomial plots, bandwidth = 350. The processor productivity FE is normalized to have the mean and standard deviation of processor output, and the supplier productivity FE the mean and standard deviation of team output.

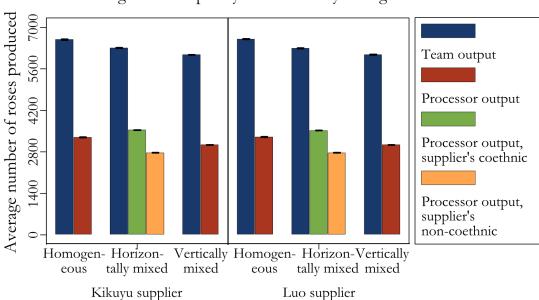


Figure 5: Output by team ethnicity configuration

95% confidence intervals are depicted. In teams with Kikuyu suppliers, average output in teams of different ethnicity configurations is as follows (standard errors in parenthesis). Team output in homogeneous teams: 6586 (12). Processor output in homogeneous teams: 3295 (8). Team output in horizontally mixed teams: 6307 (9). Processor output in horizontally mixed teams, supplier's coethnic: 3539 (8). Processor output in horizontally mixed teams: 6073 (11). Processor output in vertically mixed teams: 3039 (7). In teams with Luo suppliers, average output in teams of different ethnicity configurations is as follows (standard errors in parenthesis). Team output in homogeneous teams: 6606 (12). Processor output in homogeneous teams: 6000 (12). Processor output in homogeneous teams: 6290 (7). Processor output in horizontally mixed teams, supplier's non-coethnic: 2707 (7). Team output in teams of different ethnicity configurations is as follows (standard errors in parenthesis). Team output in homogeneous teams: 6000 (12). Processor output in homogeneous teams: 6000 (12). Processor output in horizontally mixed teams: 6290 (7). Processor output in horizontally mixed teams: 6290 (7). Processor output in vertically mixed teams: 6075 (12). Processor output in vertically mixed teams: 3037 (7)

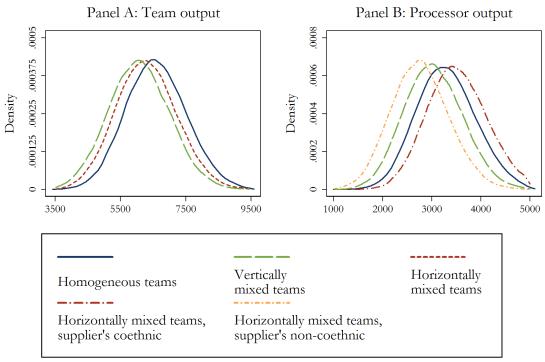


Figure 6: Distribution of output by team ethnicity configuration

Data from 2007

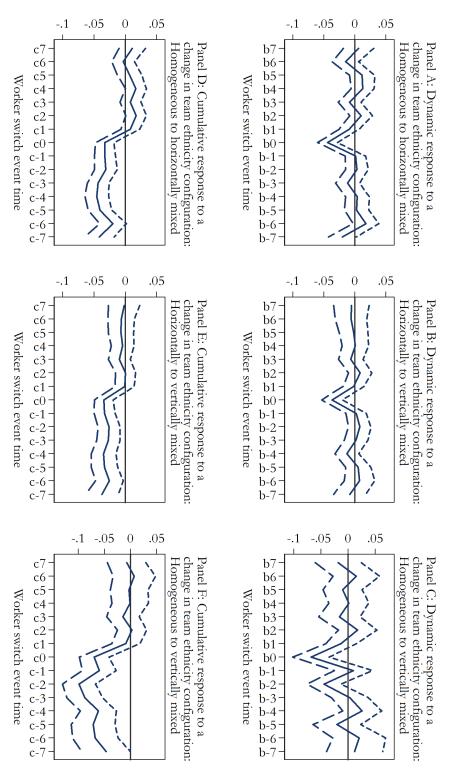
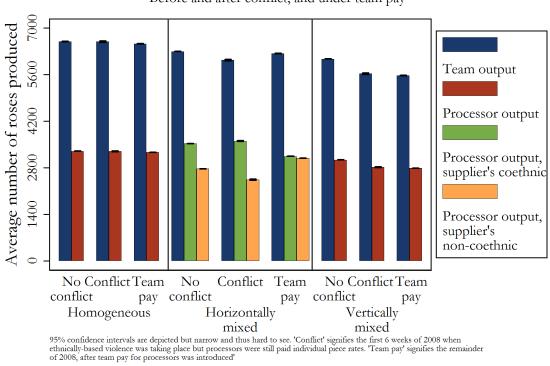
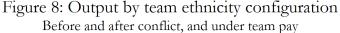
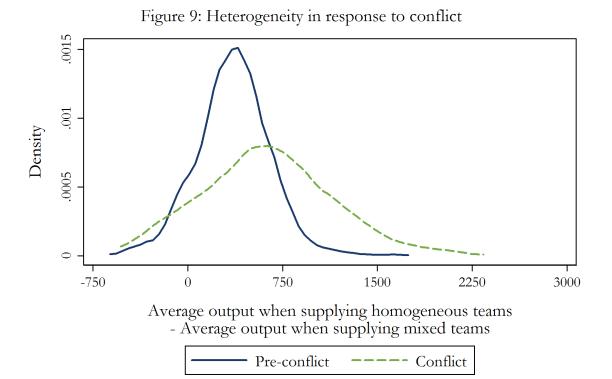


Figure 7: Team output responses to changes in team ethnicity configuration

Data from 2007. In panels A - C we plot the estimated coefficients from a regression of the first difference (across days) in output on an indicator for a worker switch entailing a change in team ethnicity configuration and its lead and lag terms (the other two workers on the team are unchanged). For example, b1 is the coefficient on the 7th lead term. In panels D - F we plot the cumulative response. The dotted lines represent 95 percent confidence intervals.







An observation is the output differential of a given supplier across homogeneous and mixed teams

Tables

100	510 1		
Sample sum	nary statistics		
	Whole sample	Kikuyu	Luo
	(N=924)	(N=426)	(N=498)
Ethnicity (% Kikuyu)	0.46		
	(0.50)		
Gender (% female)	0.59	0.57	0.61
	(0.49)	(0.49)	(0.49)
Age (average age)	34.63	34.55	34.82
	(5.21)	(5.15)	(5.29)
Experience (average years of tenure)	5.49	5.62	5.38
	(1.48)	(1.38)	(1.51)

Table 1

Standard deviations in parentheses. Individuals of the Kikuyu, Embu, Meru, Kamba, Maasai and Kisii tribes are considered "Kikuyu" and those of the Luo, Luhya and Kalenjin tribes "Luo".

Table 2 Testing for systematic team assignment

Characteristics listed in the following order: Tribe (Kikuyu = 1), Gender (Female = 1), Productivity (Above median = 1). Top number in cell: observed proportion. Bottom number (in parenthesis): proportion expected under random assignment.

]	Process	or 1			
		$0,\!0,\!0$	0,0,1	$0,\!1,\!0$	0,1,1	$1,\!0,\!0$	$1,\!0,\!1$	$1,\!1,\!0$	$1,\!1,\!1$	TOTAL
	$0,\!0,\!0$	0.011	0.013	0.013	0.016	0.012	0.011	0.016	0.013	0.104
		(0.011)	(0.011)	(0.015)	(0.018)	(0.011)	(0.010)	(0.016)	(0.012)	
	$0,\!0,\!1$	0.009	0.011	0.015	0.018	0.011	0.012	0.016	0.015	0.106
		(0.012)	(0.012)	(0.015)	(0.018)	(0.011)	(0.010)	(0.016)	(0.012)	
\mathbf{S}	$0,\!1,\!0$	0.015	0.019	0.021	0.025	0.017	0.014	0.020	0.014	0.145
\mathbf{u}		(0.016)	(0.016)	(0.021)	(0.025)	(0.015)	(0.014)	(0.022)	(0.016)	
\mathbf{p}	$0,\!1,\!1$	0.020	0.022	0.025	0.033	0.020	0.018	0.032	0.021	0.189
\mathbf{p}		(0.021)	(0.021)	(0.027)	(0.032)	(0.020)	(0.018)	(0.029)	(0.022)	
1	$1,\!0,\!0$	0.011	0.010	0.015	0.020	0.011	0.008	0.016	0.012	0.103
i		(0.011)	(0.011)	(0.015)	(0.018)	(0.011)	(0.010)	(0.016)	(0.012)	
\mathbf{e}	$1,\!0,\!1$	0.012	0.009	0.015	0.016	0.009	0.007	0.015	0.011	0.093
\mathbf{r}		(0.010)	(0.010)	(0.013)	(0.016)	(0.010)	(0.009)	(0.014)	(0.010)	
	$1,\!1,\!0$	0.018	0.013	0.021	0.025	0.015	0.014	0.018	0.016	0.140
		(0.016)	(0.015)	(0.020)	(0.024)	(0.015)	(0.013)	(0.021)	(0.016)	
	$1,\!1,\!1$	0.014	0.013	0.019	0.019	0.013	0.010	0.020	0.013	0.120
		(0.013)	(0.013)	(0.017)	(0.021)	(0.013)	(0.011)	(0.018)	(0.014)	
	TOTAL	0.110	0.109	0.144	0.171	0.107	0.093	0.152	0.114	
	p-valu	ues:	Whole	e sampl	e period	Pre-co	onflict	Conflict	Tea	m pay

0.34

0.84

0.37

0.48

(the table continues below)

Table 2 (co	ontinued)
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]	Process	or 2			
	$0,\!0,\!0$	$0,\!0,\!1$	$0,\!1,\!0$	0,1,1	$1,\!0,\!0$	$1,\!0,\!1$	$1,\!1,\!0$	$1,\!1,\!1$	TOTAL
$0,\!0,\!0$	0.013	0.010	0.018	0.017	0.012	0.012	0.015	0.014	0.110
	(0.011)	(0.011)	(0.017)	(0.020)	(0.012)	(0.010)	(0.016)	(0.014)	
0,0,1	0.009	0.010	0.018	0.023	0.011	0.010	0.014	0.013	0.109
	(0.011)	(0.011)	(0.017)	(0.020)	(0.012)	(0.010)	(0.016)	(0.013)	
$0,\!1,\!0$	0.014	0.015	0.025	0.022	0.015	0.013	0.024	0.018	0.144
	(0.014)	(0.015)	(0.022)	(0.026)	(0.015)	(0.014)	(0.021)	(0.018)	
0,1,1	0.015	0.021	0.026	0.029	0.017	0.016	0.025	0.021	0.171
	(0.017)	(0.017)	(0.026)	(0.031)	(0.018)	(0.016)	(0.025)	(0.021)	
$1,\!0,\!0$	0.011	0.013	0.015	0.019	0.011	0.010	0.015	0.013	0.107
	(0.011)	(0.011)	(0.016)	(0.019)	(0.011)	(0.010)	(0.015)	(0.013)	
$1,\!0,\!1$	0.009	0.010	0.015	0.018	0.008	0.008	0.014	0.012	0.093
	(0.009)	(0.009)	(0.014)	(0.017)	(0.010)	(0.009)	(0.013)	(0.011)	
$1,\!1,\!0$	0.017	0.011	0.021	0.027	0.020	0.015	0.022	0.018	0.152
	(0.015)	(0.015)	(0.023)	(0.027)	(0.016)	(0.014)	(0.022)	(0.019)	
$1,\!1,\!1$	0.012	0.011	0.015	0.023	0.013	0.010	0.016	0.014	0.114
	(0.011)	(0.011)	(0.017)	(0.020)	(0.012)	(0.011)	(0.016)	(0.014)	
TOTAL	0.100	0.100	0.152	0.179	0.107	0.094	0.145	0.123	
p-valı	ies:	Whole	e sampl	e period	Pre-ce	$\mathbf{onflict}$	Conflict	Tea	m pay
			0.27		0.	24	0.24	0	.50
	0,0,1 0,1,0 0,1,1 1,0,0 1,0,1 1,1,0 1,1,1 TOTAL	$ \begin{array}{c cccc} 0,0,0 & \hline 0.013 \\ (0.011) \\ 0,0,1 & 0.009 \\ (0.011) \\ 0,1,0 & 0.014 \\ (0.014) \\ 0,1,1 & 0.015 \\ (0.017) \\ 1,0,0 & 0.011 \\ (0.011) \\ 1,0,1 & 0.009 \\ (0.009) \\ 1,1,0 & 0.017 \\ (0.015) \\ 1,1,1 & 0.012 \\ (0.011) \\ \end{array} $	$\begin{array}{c ccccc} 0,0,0 & 0.013 & 0.010 \\ (0.011) & (0.011) \\ 0,0,1 & 0.009 & 0.010 \\ (0.011) & (0.011) \\ 0,1,0 & 0.014 & 0.015 \\ (0.014) & (0.015) \\ 0,1,1 & 0.015 & 0.021 \\ (0.017) & (0.017) \\ 1,0,0 & 0.011 & 0.013 \\ (0.011) & (0.011) \\ 1,0,1 & 0.009 & 0.010 \\ (0.009) & (0.009) \\ 1,1,0 & 0.017 & 0.011 \\ (0.015) & (0.015) \\ 1,1,1 & 0.012 & 0.011 \\ (0.011) & (0.011) \\ TOTAL & 0.100 & 0.100 \\ \end{array}$	0,0,0 0.013 0.010 0.018 (0.011) (0.011) (0.017) (0.017) 0,0,1 0.009 0.010 0.018 (0.011) (0.011) (0.017) 0,0,1 0.009 0.010 0.018 (0.011) (0.011) (0.017) 0,1,0 0.014 0.015 0.025 (0.014) (0.015) (0.022) 0,1,1 0.015 0.021 0.026 (0.017) (0.017) (0.026) 1,0,0 0.011 0.013 0.015 (0.011) (0.011) (0.016) 1,0,1 0.009 0.010 0.015 (0.017) 0.011 0.021 (0.015) (0.015) (0.023) 1,1,1 0.012 0.011 0.015 (0.011) (0.011) (0.017) 0.015 (0.011) (0.011) 0.017 0.015 (0.011) (0.011) (0.017) 0.015 (0.011)	0,0,0 0,0,1 0,1,0 0,1,1 0,0,0 0.013 0.010 0.018 0.017 (0,011) (0.011) (0.017) (0.020) 0,0,1 0.009 0.010 0.018 0.023 (0,011) (0.011) (0.017) (0.020) 0,1,0 0.014 0.015 0.025 0.022 0,1,0 0.014 0.015) (0.022) (0.026) 0,1,1 0.015 0.021 0.026 0.029 (0,017) (0.017) (0.026) (0.031) 1,0,0 0.011 0.017 (0.026) (0.031) 1,0,0 0.011 0.017 (0.026) (0.031) 1,0,1 0.011 (0.011) (0.016) (0.019) 1,0,1 0.017 0.011 0.015 0.018 (0.009) (0.009) (0.014) (0.017) 0.027 1,1,1 0.012 0.011 0.015 0.023 (0.011) (0.011) (0.017) (0.020) 0.020 TOTAL 0.100 0.100	0,0,0 0,0,1 0,1,0 0,1,1 1,0,0 0,0,0 0.013 0.010 0.018 0.017 0.012 (0,011) (0.011) (0.017) (0.020) (0.012) 0,0,1 0.009 0.010 0.018 0.023 0.011 (0,011) (0.011) (0.017) (0.020) (0.012) 0,1,0 0.014 0.015 0.025 0.022 0.015 (0,014) (0.015) (0.022) (0.026) (0.015) 0,1,1 0.015 0.021 0.026 0.029 0.017 (0,017) (0.017) (0.026) (0.013) (0.018) 1,0,0 0.011 0.013 0.015 0.019 0.011 (0,011) (0.017) (0.019) (0.011) (0.019) (0.011) 1,0,1 0.009 0.010 0.015 0.018 0.008 (0.009) (0.014) (0.017) (0.010) 0.101 1,1,0 0.017 0.011	0,0,0 0.013 0.010 0.018 0.017 0.012 0.012 0,0,1 (0.011) (0.011) (0.017) (0.020) (0.012) (0.010) 0,0,1 0.009 0.010 0.018 0.023 0.011 0.010 0,0,1 0.009 0.010 0.018 0.023 0.011 0.010 0,0,1 (0.011) (0.011) (0.017) (0.020) (0.012) (0.010) 0,1,0 0.014 0.015 0.025 0.022 0.015 0.013 0,1,1 0.015 0.021 0.026 0.029 0.017 0.016 0,1,1 0.015 0.021 0.026 0.029 0.017 0.016 0,11 0.013 0.015 0.019 0.011 0.010 1,0,0 0.011 0.013 0.015 0.018 0.008 1,0,1 0.009 0.014 (0.017) (0.010) 0.009 1,0,1 0.017 0.011 0.027	0,0,0 0,0,1 0,1,0 0,1,1 1,0,0 1,0,1 1,1,0 0,0,0 0.013 0.010 0.018 0.017 0.012 0.012 0.015 (0.011) (0.011) (0.017) (0.020) (0.012) (0.010) (0.016) 0,0,1 0.009 0.010 0.018 0.023 0.011 0.010 0.014 0,0,11 (0.011) (0.017) (0.020) (0.012) (0.010) (0.016) 0,1,0 0.014 0.015 0.025 0.022 0.015 0.013 0.024 (0.014) (0.015) (0.022) (0.026) (0.015) (0.021) 0.025 0,1,1 0.015 0.021 0.026 0.029 0.017 0.016 0.025 1,0,0 0.011 0.013 0.015 0.019 0.011 0.015 0.025 1,0,0 0.011 0.015 0.018 0.008 0.008 0.014 1,0,0 0.010 0.015	0,0,0 0,0,1 0,1,0 0,1,1 1,0,0 1,0,1 1,1,0 1,1,1 0,0,0 0.013 0.010 0.018 0.017 0.012 0.012 0.015 0.014 (0,011) (0.011) (0.017) (0.020) (0.012) (0.010) (0.014) 0.013 0,0,1 0.009 0.010 0.018 0.023 0.011 0.010 0.014 0.013 (0.011) (0.011) (0.017) (0.020) (0.012) (0.010) (0.016) (0.013) 0,1,0 0.014 0.015 0.025 0.022 0.015 0.014 0.018 0,1,1 0.015 0.021 0.026 (0.015) (0.014) (0.021) (0.018) 0,1,1 0.015 0.021 0.026 (0.029) 0.017 0.016 0.025 0.021 1,0,0 0.011 0.013 0.015 0.013 (0.021) (0.021) (0.021) 1,0,0 0.011 0.016 (0.017)

The top number in cell i, j is the observed proportion of position i / position j pairs in which the worker in position i has the 2³ characteristics listed in row i and the worker in position j the 2³ characteristics listed in column j. The bottom number is the expected proportion under the null hypothesis of independence. p-values for Pearson's chi-square statistic are shown. Because the worker rotation system leads to complex temporal correlation in team compositions and output, the assumptions required for validity of the chi-square tests would be violated if all data was used. I thus use a periodical "snapshot" of data in this table: team compositions on the first day of every month (team spells do not exceed one month). The chi-square tests are insignificant if data from other dates is used instead. Supplier - Processor 2 is not shown because the two processor positions are "interchangeable" A worker's productivity is her average output in month t - 2.

			·	
		Model predictions	to be tested	
		Model predi	ctions when	Predictions of models
		upstream w	of non-taste-based	
\Pr	oposition (see theoretical	Discriminatory	Neutral	diversity effects, when
ap	pendix)	preferences	preferences	$different^*$
2	Output of individuals	$q_{HM,C} > q_H$	$q_{HM,C} = q_H$	
	in teams of different	$> q_{VM} > q_{HM,NC}$	$= q_{VM} = q_{HM,NC}$	
	ethnicity configurations			
3	Output of teams of	$Q_H > Q_{VM}$ and	$Q_H = Q_{HM}$	
	different ethnicity	$Q_H > Q_{HM}$	$=Q_{VM}$	
	configurations			
4	Differential effect of	$\partial q_{HM,C}/\partial \alpha_s$	$\partial q_{HM,C}/\partial \alpha_s$	
	upstream capacity	$> \partial q_H / \partial \alpha_s$	$=\partial q_H/\partial \alpha_s$	
	across teams of different	$> \partial q_{VM} / \partial \alpha_s$	$=\partial q_{VM}/\partial \alpha_s$	
	ethnicity configurations	$> \partial q_{HM,NC} / \partial \alpha_s$	$=\partial q_{HM,NC}/\partial \alpha_s$	
5	Effects of change in	$\partial q_{HM,C} / \partial \theta_{NC} > 0$	N/A	No effect
	attitudes towards	$= q_H / \partial \theta_{NC}$		
	individuals of other	$> \partial q_{VM} / \partial \theta_{NC}$		
	ethnic groups	$> \partial q_{HM,NC} / \partial \theta_{NC}$		
6	Effects of group-based	$Q_H^{TP} < Q_H$	$Q_H^{TP} < Q_H$	
	pay for downstream	$Q_{VM}^{TP} < Q_{VM}$	$Q_{VM}^{TP} < Q_{VM}$	
	workers	$Q_H^{TP} > Q_{VM}^{TP}$	$Q_H^{TP} = Q_{VM}^{TP}$	
		$q_{HM,C}^{TP} = q_{HM,NC}^{TP}$	$q_{HM,C}^{TP} = q_{HM,NC}^{TP}$	$q_{HM,C}^{TP} > q_{HM,NC}^{TP}$
		$Q_{HM}^{TP} \gtrless Q_{HM}$	$Q_{HM}^{TP} < Q_{HM}$	$Q_{HM}^{TP} < Q_{HM}$

	Table 3	
Model	predictions to h	o tosto

* I refer here to models of technological, informational, or "cooperational" ethnic diversity effects as typically specified in the literature. The predictions of more intricate non-taste-based models may differ.

		Output	Table 4 by team ethnici	Table 4 Output by team ethnicity configuration	n			
Dependent variable:	Processor output	output	Team output	utput	Log (Processor output	r output)	Log (Team output	output)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	3298.970^{***}	3364.957 ***	6597.940^{***}	6729.914^{***}	8.084***	8.105^{***}	8.784***	8.806***
	(3.422)	(88.248)	(7.504)	(174.746)	(0.001)	(0.029)	(0.001)	(0.028)
Horizontally mixed			-300.192^{***}	-296.986***			-0.048***	-0.047***
			(9.193)	(8.351)			(0.001)	(0.001)
Horizontally mixed, processor	229.705^{***}	231.308^{***}			0.069^{***}	0.069^{***}		
of supplier's ethnicity	(5.057)	(4.834)			(0.002)	(0.001)		
Horizontally mixed, processor	-529.896^{***}	-528.293^{***}			-0.182^{***}	-0.182^{***}		
not of supplier's ethnicity	(4.902)	(4.744)			(0.002)	(0.002)		
Vertically mixed	-261.902^{***}	-260.200***	-523.803^{***}	-520.400^{***}	-0.086^{***}	-0.085^{***}	-0.085^{***}	-0.084^{***}
	(4.929)	(4.767)	(11.027)	(9.910)	(0.002)	(0.002)	(0.002)	(0.002)
Omitted category			Homogeneous	; team / Proces	Homogeneous team / Processor in homogeneous team	eous team		
Individual fixed effects?	NO	YES	NO	YES	NO	YES	NO	YES
Ν	199810	199810	99905	99905	199810	199810	99905	99905
Data from 2007 is used in these OLS regressions. The outcome variables are de-seasonalized, daily output quantities. The stan	b regressions. Th	e outcome varia	bles are de-seaso	nalized, daily out	tities.	The standard er	The standard errors are clustered at the team $*$	1 at the team

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Dependent variable:	Pro	cessor output
	(1)	(2)
Supplier permanent productivity	0.05***	0.07***
	(0.00)	(0.00)
Supplier permanent productivity \times Horizontally	-0.01	0.00
mixed, processor of supplier's ethnicity	(0.00)	(0.00)
Supplier permanent productivity \times Horizontally	-0.02^{***}	-0.04^{***}
mixed, processor not of supplier's ethnicity	(0.00)	(0.00)
Supplier permanent productivity \times Vertically	-0.02^{***}	-0.03^{***}
mixed	(0.00)	(0.00)
Constant	2996.41^{***}	2619.83***
	(21.38)	(24.31)
Horizontally mixed, processor of	263.12^{***}	216.49***
supplier's ethnicity	(31.03)	(28.83)
Horizontally mixed, processor not of	-389.63^{***}	-265.38^{***}
supplier's ethnicity	(30.80)	(28.89)
Vertically mixed	-154.99^{***}	-83.73***
	(31.11)	(28.98)
Omitted category	Hom	ogeneous team /
	Processor in	homogeneous team
Controls for processor permanent productivity?	NO	YES
Ν	197058	197058

Table 5
Supplier ability effect by team ethnicity configuration

Data from 2007 is used in these OLS regressions. The outcome variables are de-seasonalized, daily output quantities. Permanent productivity was estimated as described in section 4. Processor permanent productivity was normalized to have the mean and sd of processor output. Supplier permanent productivity was normalized to have the mean and sd of team output. The sample sizes are slightly reduced because the 5 workers that were observed as a supplier in less than two teams do not have an estimated fixed effect as supplier (and vv for those observed as processors in less than two teams). The standard errors are clustered at the processor×team level. * p < 0.10, ** p < 0.05, *** p < 0.01. The standard errors should be adjusted for the productivity regressors being estimated, and possible downward bias in the coefficients on the estimated fixed effects corrected for e.g. by using the Fuller estimator, but neither of those adjustments are likely to influence the statistical significance of estimates as precise as those seen here.

P = Processor, S = Supplier, Coethnic = of supplier's ethnicity. Data from 2007 is used in these OLS regressions. The outcome variables arede-seasonalized output quantities averaged within teams (where a team is defined by a specific worker as supplier and two other specific workersas processors. t thus refers to a team spell below, not a specific day). In (1) and (3) the output of the processor not being switched is used. Thestandard errors are clustered at the pair level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The fixed effects are for the pair of workers held constant. Note that regressors for all types of switches are included. Suppose that pair A goes from being in a team of ethnicity configuration X at $t-1$ to Y at t, and pair B from being in a Y team at $t-1$ to an X team at t. Rather than include separate "X to Y" and "Y to X" dummies, the regressions in this table include only "X to Y" and turn the associated dummy on at t for pair A and a $t-1$ for pair B. For both pairs the coefficient on "X to Y" reflects the difference in output between a period when the pair is in a team of configuration X and contiguous period when the pair is in a team of configuration X. For switches involving no change in ethnicity configuration, the dummy is (arbitrarily) turned on at the later of the two periods. Note that the constant reflects a weighted average of "pre" change output in teams of different ethnicity configurations. The non-standard definition of regressors in the table was used so as to ease comparison of the results with those in table 3.	Omitted category Pair fixed effect for unswitched workers? N	Horizontally mixed, processor of supplier's ethnicity to Horizontally mixed, processor not of supplier's ethnicity Horizontally mixed, processor not of supplier's ethnicity to vertically mixed Constant	Horizontally mixed to vertically mixed	Homogeneous to horizontally mixed, processor of supplier's ethnicity Homogeneous to vertically mixed	No change Homogeneous to horizontally mixed	Change in team ethnicity configuration	Dependent variable:	Table 0 Testing for ethnic diversity effects using pair fixed effects and 3rd worker s Sample: pairs of workers observed before and after the 3rd worker is replaced worker of the same permanent productivity tercile
Data from ι team is defi- lay). In (1) a ι 0.05, *** p ι that pair A . Rather than ι my on at t f the pair is in the pair is in in ethnicity age of "pre" o ease compa		Supplier Coethnic P	Coethnic P	Other P Supplier	Any Either P	Worker switched		using pair for ore and afte
2007 is used in ned by a specifi and (3) the outp < 0.01. The fix goes from being n include separa ior pair A and a n a team of conf configuration, t change output vison of the resu	Pairs of workers YES 109998	$\begin{array}{r} -746.938^{***} \\ (36.759) \\ 245.388^{***} \\ (24.361) \\ 3212.938^{***} \\ (4.551) \\ \hline \end{array}$	(33.505)	178.246^{***} (23.084) -291.193^{***}	$1.805 \\ (11.208)$	(1)	Unswitched Processor output	ixed effects and ar the 3rd work productivity t
these OLS reg c worker as sup ut of the proce- ed effects are fc g in a team of et g in a team of et te "X to Y" and te "X to Y" and in teams of dif- in teams of dif- in teams of dif-	"before" t YES 51589	677.805**** (3.516)	(36.577) -209.574*** (19.181)	(10.210) -525.040***	-5.094 (9.142) -308.462^{***}	(2)	Team output	0.1
Data from 2007 is used in these OLS regressions. The outcome variables are team is defined by a specific worker as supplier and two other specific workers ay). In (1) and (3) the output of the processor <i>not being switched</i> is used. The 0.05, *** $p < 0.01$. The fixed effects are for the pair of workers held constant. It that pair A goes from being in a team of ethnicity configuration X at $t - 1$ to Y. Rather than include separate "X to Y" and "Y to X" dummies, the regressions my on at t for pair A and a $t - 1$ for pair B. For both pairs the coefficient on the pair is in a team of configuration Y and a contiguous period when the pair is in a team of configuration Y and a contiguous period when the pair is ethnicity configuration, the dummy is (arbitrarily) turned on at the later of age of "pre" change output in teams of different ethnicity configurations. The sease comparison of the results with those in table 3.	he 3rd worker switch (see notes) YES YES 109998 51589	$\begin{array}{c} -0.245^{***}\\ (0.012)\\ 0.091^{***}\\ (0.008)\\ 8.052^{***}\\ (0.002)\end{array}$	(0.011)	0.054^{***} (0.007) -0.094^{***}	(0.000) (0.004)	(3)	Log (Unswitched Processor output)	witches by another
ne variables are specific workers <i>ed</i> is used. The s held constant. $_{1}$ X at $t-1$ to Y , the regressions ne coefficient on 1 when the pair 1 at the later of gurations. The	th (see notes) YES 51589	8.749^{***}	(0.006) -0.035^{***} (0.003)	(0.009) -0.085***	-0.000 (0.001) -0.050^{***}	(4)	Log (Team output)	

errors are clustered at the team level in columns 2, 4, and 6 and at the processor×team level in columns 1, 3, and 5. * p < 0.10, ** p < 0.05, *** p < 0.01. In this paper, Luo and Luhya workers are categorized as belonging to the Luo tribal bloc and Kikuyu workers to the Kikuyu bloc.

(14.138) (13.438) (31.737) (28.105) (0.005) (0.004) ategory Homogeneous team / Processor in homogeneous team	(14.138) (13.438) (31.737) (28.105) (0.005) (0.004)		** -0.077***	(14.360) (13.963) (0.005) (0.005)	** -336.366*** -0.133*** .	ict (14.934) (13.749) (0.005)	Horizontally mixed, processor 74.334*** 63.369*** 0.022*** 0.019***	(27.960) (24.820)		(19.536) (0.004) (0.003)	(4.747) (11.027) (9.899) (0.002) (0.002)	$-261.902^{***} - 261.551^{***} - 523.803^{***} - 523.101^{***} - 0.086^{***} - 0.086^{***}$	$(4.902) \qquad (4.735) \qquad (0.002) \qquad (0.002)$	-0.182^{***}	of supplier's ethnicity (5.057) (4.822) (0.002) (0.001)	(9.193) (8.341)	** -297.777***	(3.422) (92.667) (7.504) (220.060) (0.001) (0.029)	Constant $3298.970^{***} 3580.414^{***} 6597.94^{***} 6973.301^{***} 8.084^{***} 8.164^{***}$	(4) (5)	Dependent variable: Processor output Team Output Log (Processor output)	Table 8 Output by team ethnicity configuration before and after conflict
NO YES 224730 224730	in homogeneous team	<u> </u>	7*** -		·***		2***					***		2***				Ù	1***		g (Processor output)	r conflict
NO YES 112365 112365		(0.005) (0.005)	-0.076^{***} -0.076^{***}					(0.004) (0.004)	*	(0.003) (0.003)	(0.002) (0.002)	-0.085^{***} -0.085^{***}				(0.001) (0.001)	-0.048^{***} -0.047^{***}	(0.001) (0.036)	8.784*** 8.844***		Log (Team output)	

υı errors are clustered at the team level in columns 3, 4, 7 and 8, and at the processor × team level in columns 1, 2, 5, and 6. * p < 0.10, ** p < 0.05, *** p < 0.01.

Data from 2008 is used in these OLS regressions. The outcome variables are de-sesonalized, daily output quantities. The standard errors are clustered at the	Ν	Individual fixed effects?	Omitted category		Vertically mixed× Team pay	of supplier's ethnicity× Team pay	Horizontally mixed, processor not	of supplier's ethnicity× Team pay	Horizontally mixed, processor		Horizontally mixed × Team pay		Team pay		Vertically mixed	not of supplier's ethnicity	Horizontally mixed, processor	of supplier's ethnicity	Horizontally mixed, processor		Horizontally mixed		Constant		Dependent variable:	
gressions. The	204148	NO		(14.110)	1.351	(14.407)	679.396^{***}	(14.912)	-425.545^{***}			(9.989)	-30.283^{***}	(13.277)	-480.064^{***}	(13.524)	-855.296***	(14.088)	304.039^{***}			(9.391)	3295.502^{***}	(1)	Processor output	Output by
outcome variab	204148	\mathbf{YES}		(13.466)	1.112	(13.913)	682.720***	(13.851)	-422.222^{***}			(9.346)	-32.151^{***}	(12.636)	-486.560***	(13.130)	-864.142^{***}	(13.058)	295.194^{***}			(80.633)	3325.549^{***}	(2)	output	team ethnicity
les are de-sesor	102074	NO		(31.811)	2.701					(28.200)	253.850 ***	(22.804)	-60.566^{***}	(29.804)	-960.129^{***}					(26.458)	-551.257***	(21.388)	6591.003^{***}	(3)	Team output	Table 9 Output by team ethnicity configuration before and after team
alized, daily ou	102074	\mathbf{YES}	Homogeneous teams	(28.522)	2.224					(25.287)	260.498^{***}	(20.059)	-64.302^{***}	(26.616)	-973.121^{***}					(23.745)	-568.948 ** *	(160.105)	6651.097 * * *	(4)	utput	1 before and a
utput quantities	204148	NO	us teams	(0.005)	-0.002	(0.005)	0.258^{***}	(0.004)	-0.130^{***}			(0.003)	-0.010^{***}	(0.004)	-0.163^{***}	(0.005)	-0.316^{***}	(0.004)	0.090 * * *			(0.003)	8.083^{***}	(5)	Log (Processor output)	fter team pay
s. The standard	204148	\mathbf{YES}		(0.005)	-0.001	(0.005)	0.260^{***}	(0.004)	-0.128^{***}			(0.003)	-0.010^{***}	(0.004)	-0.165^{***}	(0.005)	-0.319^{***}	(0.004)	0.087^{***}			(0.029)	8.085***	(6)	or output)	
l errors are clu	102074	NO		(0.005)	-0.001					(0.004)	0.043^{***}	(0.004)	-0.010^{***}	(0.005)	-0.161^{***}					(0.004)	-0.090***	(0.003)	8.783***	(7)	Log (Team	
stered at the	102074	YES		(0.005)	-0.001					(0.004)	0.044^{***}	(0.003)	-0.011^{***}	(0.004)	-0.163^{***}					(0.004)	-0.093^{***}	(0.028)	8.790***	(8)	(Team output)	

team level in columns 3, 4, 7 and 8, and at the processor×team level in columns 1, 2, 5, and 6. * p < 0.10, ** p < 0.05, *** p < 0.01.

	Supplier lost	Supplier did not	Supplier	Supplier
Sample:	relative	lose relative	young	old
Dependent variable:		Team output	t	
	(1)	(2)	(3)	(4)
Constant	6564.04***	6608.01***	6593.77**	**6602.07**
	(16.03)	(8.48)	(10.78)	(10.45)
Horizontally mixed	-286.25^{***}	-304.21^{***}	-263.82^{**}	**-336.66**
	(19.50)	(10.42)	(13.01)	(12.97)
Vertically mixed	-474.25^{***}	-538.01^{***}	-390.33^{**}	**-660.79**
	(23.57)	(12.47)	(15.05)	(15.21)
Conflict	61.26	-26.00	1.42	-15.18
	(47.55)	(25.64)	(32.67)	(31.33)
Horizontally mixed \times	-329.46^{***}	-230.85^{***}	-279.78*	**-223.44**
Conflict	(59.27)	(31.63)	(39.49)	(39.65)
Vertically mixed \times	-584.96^{***}	-402.41^{***}	-567.77^{**}	**-301.22**
Conflict	(77.47)	(35.07)	(43.71)	(45.62)
Omitted category		Homogeneous te	eams	
Ν	24860	87505	56432	55933

 Table 10

 Heterogeneity in effect of conflict on discriminatory behavior

Data from 2007 and the first six weeks of 2008 is used in these OLS regressions. The outcome variables are de-seasonalized, daily output quantities. * p < 0.10, ** p < 0.05, *** p < 0.01. The standard errors are clustered at the team level.

	Period: No conflict											
Output-maximizing		Produc	tivity	Ethnicity and								
assignment by:	Ethnicity	as P a	and S	productivity as P and S								
Assignment	Homogeneous 100%	s2p3p3	50.64%	Homogeneous,s2p1p2	17.53%							
		s3p1p2	49.03%	${\rm Homogeneous}, {\rm s3p1p2}$	31.82%							
Output gains		s3p1p3	0.32%	Homogeneous,s3p3p3	50.65%							
relative to:												
random	4.4%	3.54%		9.19%								
assignment												
output-minimizing	8.6%	7.13%		16.38%								
assignment												
		Perie	od: Confl	ict								
Output-maximizing		Produc		Ethnicity and								
assignment by:	Ethnicity	as P a	and S	productivity as P and S								
Assignment	Homogeneous 100%	s2p2p3	0.65%	${\rm Homogeneous, s2p1p2}$	28.90%							
		s2p3p3	50.32%	Homogeneous,s3p1p1	18.18%							
		s3p1p1	34.32%	${\rm Homogeneous}, s3p2p3$	4.55%							
Output gains		s3p2p2	14.61%	Homogeneous,s3p3p3	48.38%							
relative to:												
random	8.2%	4.33%		15.37%								
assignment												
output-minimizing	$17 \ \%$	8.47%		30.10%								
assignment												
			d: Team									
Optimal		Produc		Ethnicity and								
assignment by:	Ethnicity	as P a		productivity as P and S								
Assignment	Homogeneous 100%	s2p1p3	0.32%	Homogeneous,s2p3p3	44.48%							
		s2p3p3	50.65%	Homogeneous,s3p1p1	34.42%							
		s3p1p1	19.16%	${\rm Homogeneous, s3p2p2}$	14.94%							
Output-maximizing		s3p2p2	29.87%	Homogeneous,s3p3p3	6.17%							
assignment by:												
random	6.4%	3.42%		10.65%								
assignment												
output-minimizing	$17 \ \%$	7.13%		24.85%								
assignment												

Table 11 Output gains from optimal assignment by ethnicity, productivity or both

sX = supplier productivity of tercile X. pX analogous (only productivity tercile in assigned position is shown). The team type configuration that the average output associated with all types of teams and the "budget set" of workers available suggests will maximize output is displayed. The procedure is described in the empirical appendix.

Sample, tenure:	А	.11	Below median tenure							
Sample,	Supplier	Supplier	Supplier	Supplier						
previous interaction	interaction $w/$	interaction $w/$	interaction $w/$	interaction w/ $$						
	$\operatorname{non-coethnics}$	$\operatorname{non-coethnics}$	$\operatorname{non-coethnics}$	$\operatorname{non-coethnics}$						
	low	high	low	high						
Dependent variable:		Team	output							
	(1)	(2)	(3)	(4)						
Constant	6612.00***	6579.56^{***}	6575.20***	6595.34^{***}						
	(14.66)	(14.57)	(19.20)	(21.91)						
Horizontally mixed	-307.34^{***}	-275.16^{***}	-312.52^{***}	-294.89^{***}						
	(18.12)	(17.86)	(24.28)	(27.00)						
Vertically mixed	-536.23^{***}	-504.28^{***}	-536.14^{***}	-492.12^{***}						
	(22.46)	(20.45)	(29.01)	(31.19)						
Conflict	-20.81	11.24	0.03	-27.91						
	(33.73)	(33.20)	(43.19)	(51.55)						
Horizontally mixed \times	-258.85^{***}	-263.32^{***}	-263.39^{***}	-270.99^{***}						
Conflict	(41.34)	(41.23)	(53.96)	(65.68)						
Vertically mixed \times	-437.18^{***}	-446.72^{***}	-442.10^{***}	-446.37^{***}						
Conflict	(48.82)	(45.58)	(69.34)	(67.83)						
Omitted category	Homogeneous teams									
N	29634	32642	15132	13582						

Table 12 Effect of previous interaction with workers of other ethnic groups on discriminatory behavior before and during conflict

Data from 2007 and the first six weeks of 2008 is used in these OLS regressions. The outcome variables are de-seasonalized, daily output quantities. The standard errors are clustered at the team level. * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix

A1. Theoretical Appendix

In addition to the assumptions in section 3, I make the following assumptions. Let $q_p = f(e_{sp}, \alpha_s, e_p, \alpha_p) = (e_p \alpha_p)^{\beta} (e_{sp} \alpha_s)^{\gamma}$. β then measures the slope of processor output in processor ability and effort, and γ the slope in supplier ability and effort. The ability terms are assumed to be positive, and q_p concave in processor and supplier effort. q_p is also assumed to display decreasing returns: $0 < \beta < 1$, $0 < \gamma < 1$, $\beta + \gamma < 1$. The processor's effort carries costs $\frac{1}{2}e_1^2$, and the total effort of the supplier $\frac{1}{2}(e_{s1} + e_{s2})^2$. I assume that $\alpha_p > 1$, $\alpha_s > 1$ and $-\frac{1}{2} < \theta_p < \frac{1}{2}$.³⁸ I also assume that suppliers do not take ethnicity as a signal of ability.

Consider first the processor's problem, focusing here on processor 1 (processor 2's problem is analogous). A processor maximizes her benefit of pay minus her cost of effort:

$$\operatorname{Max}_{e_1} 2w(e_1\alpha_1)^{\beta}(e_{s_1}\alpha_s)^{\gamma} - \frac{1}{2}e_1^2$$

s.t. $e_1 \ge 0$

which gives

$$e_1 = \left(2w\beta(e_{s1}\alpha_s)^{\gamma}\alpha_1^{\beta}\right)^{\frac{1}{2-\beta}}$$

Processor effort is thus increasing in processor and supplier ability and in the supplier's effort. Note that the processor's effort choice depends on the supplier's weight on her utility only through its influence on her supply of intermediate flowers.

A supplier maximizes her benefit of pay minus her cost of effort plus the additional utility (or disutility) she derives from the well-being of each of the processors:

$$\begin{aligned} & \underset{e_{s1},e_{s2}}{\text{Max}} \quad w((e_{1}\alpha_{1})^{\beta}(e_{s1}\alpha_{s})^{\gamma} + (e_{2}\alpha_{2})^{\beta}(e_{s2}\alpha_{s})^{\gamma}) - \frac{1}{2}(e_{s1} + e_{s2})^{2} \\ & \quad + \theta_{1} \left(2w(e_{1}\alpha_{1})^{\beta}(e_{s1}\alpha_{s})^{\gamma} - \frac{1}{2}e_{1}^{2} \right) + \theta_{2} \left(2w(e_{2}\alpha_{2})^{\beta}(e_{s2}\alpha_{s})^{\gamma} - \frac{1}{2}e_{2}^{2} \right) \\ & \quad s.t. \quad e_{s1} \ge 0 \text{ and } e_{s2} \ge 0 \end{aligned}$$

The supplier's first order condition for e_{s1} gives

$$(e_{s1} + e_{s2}) = (1 + 2\theta_1) w (e_1 \alpha_1)^{\beta} \gamma (e_{s1} \alpha_s)^{\gamma - 1}$$

When the supplier's two first order conditions hold simultaneously,

$$e_{s1} = \left(\frac{(1+2\theta_1) w(e_1\alpha_1)^{\beta} \gamma(\alpha_s)^{\gamma-1}}{1 + \left(\frac{1+2\theta_1}{1+2\theta_2}\right)^{\frac{1}{\gamma-1}} \left(\frac{e_1\alpha_1}{e_2\alpha_2}\right)^{\frac{\beta}{\gamma-1}}}\right)^{\frac{1}{2-\gamma}}$$

Because the supplier considers the pay-off (from own pay and processors' utility) of supply to

³⁸If this restriction is violated corner solutions arise.

each of the processors, her effort devoted to supplying processor 1 is increasing in that processor's ability and utility weight, but decreasing in the ability and utility weight of the other processor.

The model has the following predictions. Because tedious algebra is involved, the proofs are in the online theoretical appendix.

Proposition 1 (Existence and comparative statics):

i. There exists a unique equilibrium in which production is given by

$$q_{1}^{*} = \frac{k_{q}\alpha_{s}^{\frac{2\gamma}{2-\beta-\gamma}}\alpha_{1}^{\frac{2\beta}{2-\beta-2\gamma}}\left(1+2\theta_{1}\right)^{\frac{2\gamma}{2-\beta-2\gamma}}}{\left(\alpha_{1}^{\frac{2\beta}{2-2\gamma-\beta}}\left(1+2\theta_{1}\right)^{\frac{2-\beta}{2-2\gamma-\beta}}+\alpha_{2}^{\frac{2\beta}{2-2\gamma-\beta}}\left(1+2\theta_{2}\right)^{\frac{2-\beta}{2-2\gamma-\beta}}\right)^{\frac{\gamma}{2-\beta-\gamma}}}$$
$$Q^{*} = \frac{k_{q}\alpha_{s}^{\frac{2\gamma}{2-\beta-\gamma}}\left(\alpha_{1}^{\frac{2\beta}{2-\beta-2\gamma}}\left(1+2\theta_{1}\right)^{\frac{2\gamma}{2-\beta-2\gamma}}+\alpha_{2}^{\frac{2\beta}{2-\beta-2\gamma}}\left(1+2\theta_{2}\right)^{\frac{2\gamma}{2-\beta-2\gamma}}\right)}{\left(\alpha_{1}^{\frac{2\beta}{2-2\gamma-\beta}}\left(1+2\theta_{1}\right)^{\frac{2-\beta}{2-2\gamma-\beta}}+\alpha_{2}^{\frac{2\beta}{2-2\gamma-\beta}}\left(1+2\theta_{2}\right)^{\frac{2-\beta}{2-2\gamma-\beta}}\right)^{\frac{\gamma}{2-\beta-\gamma}}}$$

where $k_q = (2\beta)^{\frac{\beta}{2-\gamma-\beta}} w^{\frac{\beta+\gamma}{2-\gamma-\beta}} \gamma^{\frac{\gamma}{2-\gamma-\beta}}$ and $Q = q_1 + q_2$ is team output.

ii. Processor output is increasing in own ability, the ability of the supplier and the weight the supplier attaches to her utility, but decreasing in the ability and weight of the other processor: $\frac{\partial q_1}{\partial \alpha_1} > 0, \frac{\partial q_1}{\partial \alpha_s} > 0, \frac{\partial q_1}{\partial \alpha_2} < 0, \frac{\partial q_1}{\partial \theta_1} > 0, \frac{\partial q_1}{\partial \theta_2} < 0$

In principle the θ 's vary continuously. However, to focus on the possibility of supplier discrimination, I consider a simplified case. Let $\theta_i = \theta_C$ if processor *i* is of the supplier's ethnic group, and $\theta_i = \theta_{NC}$ if not. Processors are then observed in four different positions: in homogeneous teams (*H*), in vertically mixed teams (*VM*), and in horizontally mixed teams in which the processor in question may (*HM*, *C*) or may not (*HM*, *NC*) be of the supplier's ethnic group. From a team perspective there are three types of ethnicity configurations, as illustrated in figure 1b. I then derive the following comparative propositions.

Proposition 2 (Processor output): Processor output is unaffected by the ethnicity of the supplier and the other processor if the supplier has ethnicity-neutral social preferences ($\theta_C = \theta_{NC}$): $q_H = q_{HM,C} = q_{HM,NC} = q_{VM}$. Processor output is higher (a) when working with a coethnic supplier, and (b) when working with another processor who is not of the supplier's ethnicity if the supplier has discriminatory preferences ($\theta_C > \theta_{NC}$): $q_{HM,C} > q_H > q_{VM} > q_{HM,NC}$

Ethnicity-neutral upstream workers' optimal supply to each processor is determined by the abilities of the three workers. Proposition 2 makes clear that biased supplier preferences will lead to "horizontal misallocation" - the relative supply to the two processors deviating from their relative

abilities - in horizontally mixed teams, and to "vertical misallocation" - the total quantity of roses supplied deviating from the ethnicity-neutral optimal supply - in both horizontally and vertically mixed teams. Misallocation of roses is predicted to lower team output:

Proposition 3 (Team output): Team output is unaffected by a team's ethnicity configuration if the supplier has ethnicity-neutral social preferences ($\theta_C = \theta_{NC}$): $Q_H = Q_{HM} = Q_{VM}$. Team output in homogeneous teams is higher than in mixed teams if the supplier has discriminatory preferences ($\theta_C > \theta_{NC}$): $Q_H > Q_{VM}$ and $Q_H > Q_{HM}$

Next I consider the framework's predictions for how upstream capacity is allocated across downstream workers:

Proposition 4 (Supplier ability effect): The effect of supplier ability on processor output is unaffected by a team's ethnicity configuration if the supplier has ethnicity-neutral social preferences $(\theta_C = \theta_{NC})$: $\partial q_H / \partial \alpha_s = \partial q_{HM,C} / \partial \alpha_s = \partial q_{HM,NC} / \partial \alpha_s = \partial q_{VM} / \partial \alpha_s$. Higher supplier ability benefits processor output more (a) when working with a coethnic supplier, and (b) when working with another processor who is not of the supplier's ethnic group if the supplier has discriminatory preferences $(\theta_C > \theta_{NC})$: $\partial q_{HM,C} / \partial \alpha_s > \partial q_H / \partial \alpha_s > \partial q_{VM} / \partial \alpha_s > \partial q_{HM,NC} / \partial \alpha_s$

Biased, higher-ability suppliers allocate more of their additional capacity to supplying coethnic processors because they derive greater benefits from coethnics' output.

It is possible that the period of ethnic conflict in Kenya in early 2008 led to a change in attitudes towards co-workers of the other ethnic group, which I model as a change in θ_{NC} :

Proposition 5 (Change in preferences): A decrease in the weight attached to the wellbeing of non-coethnics leads to an increase in the output of the processor of the supplier's ethnicity in horizontally mixed teams, no change in the output of processors in homogeneous teams, and a decrease in the output of processors who are not of the supplier's ethnicity. The decrease is greater for non-coethnic processors in horizontally mixed teams: $\partial q_{HM,C}/\partial \theta_{NC} < 0 = q_H/\partial \theta_{NC} \leq$ $\partial q_{VM}/\partial \theta_{NC} \leq \partial q_{HM,NC}/\partial \theta_{NC}$

If the gap between the weight attached to coethnics' and non-coethnics' well-being widens, so does the output gap between teams of different ethnicity configurations.

Six weeks into the conflict period the plant began paying processors for their combined output. Under such a pay system a processor's utility from pay is $w(q_1 + q_2)$, rather than $2wq_1$ as under individual pay. Processor 1's problem becomes:

$$\underset{e_1}{\text{Max}} w \left((e_1 \alpha_1)^{\beta} (e_{s_1} \alpha_s)^{\gamma} + (e_2 \alpha_2)^{\beta} (e_{s_2} \alpha_s)^{\gamma} \right) - \frac{1}{2} e_1^2$$

s.t. $e_1 \ge 0$

which gives

$$e_1 = \left(w\beta(e_{s1}\alpha_s)^{\gamma}\alpha_1^{\beta}\right)^{\frac{1}{2-\beta}}$$

Under team pay the supplier solves

$$\begin{aligned} \underset{e_{s1},e_{s2}}{\text{Max}} & w((e_{1}\alpha_{1})^{\beta}(e_{s1}\alpha_{s})^{\gamma} + (e_{2}\alpha_{2})^{\beta}(e_{s2}\alpha_{s})^{\gamma}) - \frac{1}{2}(e_{s1} + e_{s2})^{2} \\ & + w(\theta_{1} + \theta_{2})((e_{1}\alpha_{1})^{\beta}(e_{s1}\alpha_{s})^{\gamma} + (e_{2}\alpha_{2})^{\beta}(e_{s2}\alpha_{s})^{\gamma}) - \theta_{1}\frac{1}{2}e_{1}^{2} - \theta_{2}\frac{1}{2}e_{2}^{2} \\ & s.t. \quad e_{s1} \ge 0 \text{ and } e_{s2} \ge 0 \end{aligned}$$

The supplier's first order condition for e_{s1} gives

$$e_{s1} + e_{s2} = w(1 + \theta_1 + \theta_2)(e_1\alpha_1)^{\beta}\gamma(e_{s1}\alpha_s)^{\gamma-1}\alpha_s$$

When the supplier's two first order conditions hold simultaneously,

$$e_{s1} = \left(\frac{w(1+\theta_1+\theta_2)\gamma (e_1\alpha_1)^{\beta} \alpha_s^{\gamma}}{1+\left(\frac{e_2\alpha_2}{e_1\alpha_1}\right)^{\frac{\beta}{1-\gamma}}}\right)^{\frac{1}{2-\gamma}}$$

Because effort devoted to supplying one processor benefits both processors under team pay, the supplier's effort in supplying processor 1 is increasing in both θ_1 and θ_2 . If the two processors are of the same ability $e_{s1} = e_{s2}$ under team pay.

Solving the model under team pay gives the following predictions:

Proposition 6 (Team pay):

i. There exists a unique equilibrium under team pay in which production is given by

$$q_1^{TP*} = \frac{k_q^{TP} \alpha_s^{\frac{\gamma}{2-\beta-\gamma}} \alpha_p^{\frac{2\beta}{2-\beta-2\gamma}} (1+\theta_1+\theta_2)^{\frac{\gamma}{2-\beta-\gamma}}}{\left(\alpha_1^{\frac{2\beta}{2-2\gamma-\beta}} + \alpha_2^{\frac{2\beta}{2-2\gamma-\beta}}\right)^{\frac{\gamma}{2-\beta-\gamma}}}$$
$$Q^{TP*} = k_q^{TP} \alpha_s^{\frac{\gamma}{2-\beta-\gamma}} \left(\alpha_1^{\frac{2\beta}{2-2\gamma-\beta}} + \alpha_2^{\frac{2\beta}{2-2\gamma-\beta}}\right)^{\frac{2-\beta-2\gamma}{2-\beta-\gamma}} (1+\theta_1+\theta_2)^{\frac{\gamma}{2-\beta-\gamma}}$$
$$P = \gamma^{\frac{\gamma}{2-\beta-\gamma}} w^{\frac{\beta+\gamma}{2-\beta-\gamma}} \beta^{\frac{\beta+2\gamma}{2-\beta-\gamma}}.$$

where k_a^T

- ii. Output in homogeneous and vertically mixed teams falls when team pay is introduced: $Q_H^{TP} <$ Q_H and $Q_{VM}^{TP} < Q_{VM}$
- iii. Output in homogeneous teams will continue to exceed that in vertically mixed teams under team pay if suppliers have discriminatory preferences ($\theta_C > \theta_{NC}$): $Q_H^{TP} > Q_{VM}^{TP}$
- iv. The output of the processor of the supplier's ethnicity and the processor who is not of the supplier's ethnicity in horizontally mixed teams is equal under team pay, even if suppliers have ethnic preferences ($\theta_C > \theta_{NC}$): $q_{HM,C}^{TP} = q_{HM,NC}^{TP}$

v. Output in horizontally mixed teams Q_{HM}^{TP} can decrease or increase when team pay is introduced if suppliers have discriminatory preferences ($\theta_C > \theta_{NC}$): $Q_{HM}^{TP} \ge Q_{HM}$

In scenarios in which the two downstream workers are of the same ethnic group - homogeneous and vertically mixed teams - the supplier's problem reduces to the same problem she faced under individual pay. In such teams equilibrium production falls under team pay as processors freeride on each other. $Q_H > Q_{VM}$ is expected to continue to hold because biased suppliers' incentive to discriminate against non-coethnics through total supply remains under team pay.

In addition to the negative freeriding effect, team pay is expected to have an offsetting positive effect in horizontally mixed teams, in which $\theta_1 \neq \theta_2$. Because the two processors in a team are paid the same under team pay, the supplier is unable to increase her own utility by "shifting" roses from less to more favored processors. Eliminating horizontal misallocation will positively affect team output.

A2. Empirical Appendix

A2a. Estimation of utility-weights

I estimate the ratio-of-ratios on a sample of horizontally mixed teams in which a supplier is followed by another supplier of the other ethnic group. Instead of comparing the change in output from one day to the next, I compare average output under the first supplier, s = 0, to average output under the second supplier, s = 1. The log of the numerator of the left-hand side of the ratio-of-ratios is regressed on the log of the denominator and a constant:

$$\log(q_{1,\overline{s=0}}/q_{2,\overline{s=0}}) = \lambda + \eta \log(q_{1,\overline{s=1}}/q_{2,\overline{s=1}}) + \varepsilon$$
(1)

The resulting $\hat{\lambda}$ can be interpreted as an estimate of $\log((1+2\theta_1/1+2\theta_2)^{\frac{4\gamma}{2-\beta-2\gamma}})$. Arranging the data such that $\log((1+2\theta_1/1+2\theta_2)^{\frac{4\gamma}{2-\beta-2\gamma}}) = \log((1+2\theta_C/1+2\theta_{NC})^{\frac{4\gamma}{2-\beta-2\gamma}})$ and estimating (1) on pre-conflict data gives $\hat{\lambda} = 0.36$. $\hat{\lambda}'$, from estimating (1) on data from the conflict period, is 0.52. Both estimates are significantly greater than zero at the 1% level.

Noting that $\hat{\theta}_C = \frac{1}{2} \left(\left(\exp(\hat{\lambda}) \right)^{\frac{2-\beta-2\gamma}{4\gamma}} \left(1 + 2\hat{\theta}_{NC} \right) - 1 \right)$, with $\hat{\lambda}$ in hand we can evaluate the locus of pairs of utility-weights that can explain the observed change in output when a supplier of one ethnic group replaces a supplier of the other ethnic group. Focusing on the pre-conflict period, suppose for example that $\beta = \gamma = 0.3$. Consider four possibilities: $(\theta_C > 0 \text{ and } \theta_{NC} = 0)$, $(\theta_C = 0, \theta_{NC} < 0)$, $(\theta_C > 0 \text{ and } \theta_{NC} > 0)$, $(\theta_C > 0, \theta_{NC} < 0)$. In the first two cases, $\hat{\lambda} = 0.36$ implies $\hat{\theta}_C \approx 0.19$ and $\hat{\theta}_{NC} \approx -0.14$, respectively. In the latter two cases, further assumptions are required. If both preference parameters are positive, $\theta_C = 0.25$ implies $\hat{\theta}_{NC} \approx 0.04$ while $\theta_C = 0.4$ implies $\hat{\theta}_{NC} \approx 0.15$. If individuals attach positive weight to the well-being of coethnics and negative to the well-being of non-coethnics, suppose that $|\theta_C| = |\theta_{NC}|$. In that case $\hat{\theta}_C \approx 0.08, \hat{\theta}_{NC} \approx -0.08$.

Suppose that θ_C did not change when conflict began, as the results of table 8 suggest. Then,

$$1 = \frac{\widehat{\theta}_C}{\widehat{\theta}'_C} = \frac{\frac{1}{2} \left(\left(\exp(\widehat{\lambda}) \right)^{\frac{2-\beta-2\gamma}{4\gamma}} \left(1 + 2\widehat{\theta}_{NC} \right) - 1 \right)}{\frac{1}{2} \left(\left(\exp(\widehat{\lambda}') \right)^{\frac{2-\beta-2\gamma}{4\gamma}} \left(1 + 2\widehat{\theta}'_{NC} \right) - 1 \right)}$$

which gives

$$\theta_{NC}' = \frac{1}{2} \left(\frac{1 + 2\widehat{\theta}_{NC}}{\left(\exp(\widehat{\lambda}' - \widehat{\lambda}) \right)^{\frac{2-\beta-2\gamma}{4\gamma}}} - 1 \right) = \frac{1}{2} \left(\frac{1 + 2\widehat{\theta}_{NC}}{\left(\exp(0.16) \right)^{\frac{2-\beta-2\gamma}{4\gamma}}} - 1 \right)$$

Assumptions on θ_{NC} , β and γ are need to bound $\Delta \theta_{NC}$; I consider a wide parameter space. Given the plant's chosen triangular organization of production, β and γ are arguably likely to be of similar magnitude. Consider $\beta \in \left[\frac{1}{3}, \frac{2}{3}\right]$, $\gamma \in \left[\frac{1}{3}, \frac{2}{3}\right]$ (subject to $\beta + \gamma < 1$). Letting $\theta_{NC} \in [-0.15, 0.15]$, $\beta = \gamma = \frac{1}{3}$ gives $\Delta \theta_{NC} \in [-0.07, -0.04]$ and $\Delta \theta_{NC}/\theta_{NC} \in [-1.27, -0.27]$. $\beta = \frac{1}{3}$, $\gamma = \frac{2}{3}$ gives $\Delta \theta_{NC} \approx -0.01$ and $\Delta \theta_{NC}/\theta_{NC} \in [-0.23, -0.09]$. $\beta = \frac{2}{3}, \gamma = \frac{1}{3}$ gives $\Delta \theta_{NC} \in [-0.23, -0.09]$. [-0.05, -0.03] and $\Delta \theta_{NC}/\theta_{NC} \in [-0.71, -0.32]$. Averaging across the parameter space considered gives the bounds and average $\Delta \theta_{NC}/\theta_{NC}$ noted in the paper.

A2b. Optimal assignment procedure

I briefly describe the procedure used to compute the optimal assignments in table 11. See Bhattacharya (2009) for a more detailed description and justification of the procedure. The goal is to maximize the total output of a set of workers with multiple discrete characteristics. Discreteness implies a finite number of worker types, which can be combined into a finite number of team types. Output is maximized by choosing the quantities of each type of team that gives the highest total output, subject to the quantities of each worker type available. A solution to such a system is obtained using integer linear programming.

A worker is fully characterized by a collection of three discrete attributes: tribe, productivity tercile as supplier, and productivity tercile as processor. In turn, the set of possible team types is derived from the set of possible worker types. A team consists of one type of worker as supplier, one type of worker as processor 1, and one type of worker as processor 2.

The two processor positions are considered to be equivalent, and thus the number of processor pairs is calculated as two unordered draws with replacement from the pool of possible workers. There are $\binom{18+2-1}{2} = 171$ ways that these two can be chosen. Combining those with the 18 possibilities for the supplier gives 3078 distinct types of teams, if all possible types were to be considered. Those 3078 team types are mapped into 18 output coefficients when assignment is by productivity, and 63 output coefficients when assignment is by both productivity and tribe, as described in the paper.

An output-maximizing assignment is the solution of an integer linear programming problem with the following objective function:

$$\underset{t_1,\ldots,t_{3078}}{\operatorname{Max}}Q = \sum_{i=1}^{3078} \overline{Q}_i t_i$$

Each t_i term represents a possible type of team that can be formed from three workers, and \overline{Q}_i is the average output of that type of team.

The maximization of the objective function is constrained by the number of each type of worker that is present at the plant. For each worker type w_j , a constraint equates the number of workers used with the number of workers in the workforce:

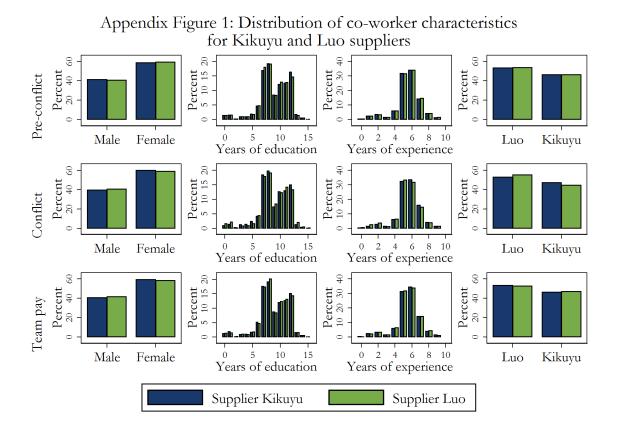
$$\sum \{t_i | \text{there is 1 } w_j \text{ worker in } t_i \}$$

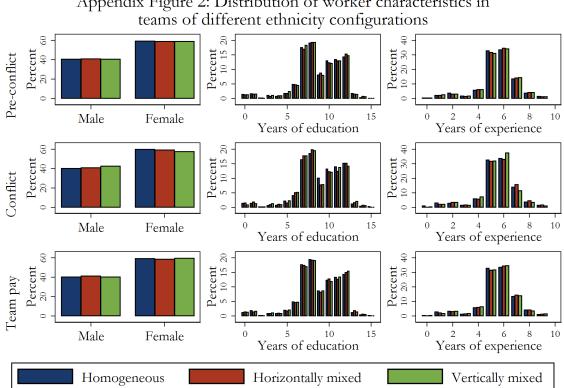
+ 2 \sum \{t_i | \there are 2 \widshifty workers in t_i \}
+ 3 \sum \{t_i | \there are 3 \widshifty workers in t_i \} = \widshifty w_j

The result of building these constraints is an 18×3078 matrix equation for which the columns represent team types and the rows worker types.

The optimal assignments in table 11 were obtained by solving these problems using the Gurobi solver. The output associated with "random assignment" in the table was computed by drawing 300 random assignments and taking the average output of those.

Appendix Figures





Appendix Figure 2: Distribution of worker characteristics in