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# Diversity, discrimination, and performance

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#### **Abstract:**

Employee diversity may affect business performance both as a result of customer discrimination and as a result of how members of a group work with each other in teams. We test for both channels with data from more than 800 retail stores employing over 70,000 individuals, matched to Census data on the demographics of the community. We find little payoff to matching employee demographics to those of potential customers except when the customers do not speak English. Diversity of race or gender within the workplace does not predict sales or sales growth, although age diversity predicts low sales.

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## Diversity, Discrimination, and Performance

JonathanS.Leonard \* and DavidI.Levine \*\*

Abstract: Employeediversitymayaffectbusinessperformancebothasaresultofcustomer discriminationandasaresultofhowmembersofagroupwo rkwitheachotherinteams. We testforbothchannelswithdatafrommorethan 800 retailstoresemploying over 70,000 individuals, matched to Census data on the demographics of the community. We find little payoff to matching employeedemographics to hose of potential customers except when the customers do not speak English. Diversity of race or gender within the work placedoes not predicts also so rales growth, although age diversity predicts low sales.

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MorethantwodecadesafteremploymentdiscriminationwasoutlawedbytheCivil
RightsActof1964,theCEOofShoney's restaurantchainenteredoneofits restaurantsthat had
laggingsalesandnoticedmanyblackemployeesinvisiblepositions. Seeingthatthecustomers
were largely white, he sentame mototherestaurantmanager directing him to employmore
white supfront. In 1993, this attempt to accommodate the CEO's perceptions of customers'
discriminatory preferences resulted in a settlement for \$132 million (Watkins, 1997).

Proponentsofworkplacediversity,incontrasttotheCEOatShoney's,havefrequently claimedthatdemographicdiversityisgoodforbusiness (Cox,1993;BantelandJackson,1989). AsdidShoney'sCEO,theyoftenclaimthatcustomersprefertodealwithemployeeswhohave similardemographics. The difference between these two sets of advocates of accommodating customer discrimination is that honey's CEOsawhis potential customers as white, while diversity proponents assume the customer base is typically diverse. If customers are diverse and many customers prefer to deal with a demographically similars ales person, then employee diversity can increase sales.

Diversityproponents and opponents also make conflicting claims about how employees' similarity with each other affects performance. For example, so meclaim diversity can improve creativity and increase information (e.g., Banteland Jacks on 1989; Jehn, North craft, and Neale, 1999; Watson, Kumar, and Michaelson 1993). When creativity and the presence of diverse information sources are important, diversity can improve performance whenever work groups make decisions, reg ard less of the contact with or composition of customers. At the same time, other theories (reviewed below) emphasize how work force diversity can reduce cohesiveness and communication among employees.

Giventheseconflictinghypotheses, the fundamental question about how these conflicting forces affect the performance of actual work - groups is unanswered. One reason for the continued lack of clarity is that no large - scale studies speak directly to the seconflicting hypotheses. In this study, we use long it udinal evidence from more than 800 similar business establishments within a single very large employer to examine how the demographic match between customers and employees affects work place performance. (Due to confidentiality restrictions, we are unable to mention the name or industry of the employer.) We also examine how employees 'racial, ethnic, gender and age diversity affect work place performance.

Followingestablishmentsovertime, we can also see how changes in work placed emographics affect performance within a work place. Our measure of work place performance is an objective one of central importance to business: sales.

Ifeconomists could run a controlled experiment on diversity, we would want to replicate the same workplace, experimentally var ying only employee demographics. Although demographics have not been randomized, the workplaces are members of national chains that by design attempt to hold fixed many confounding factors that might affects a less. The chain shave attempted to replicate the sew or kplaces in every significant U.S. market.

Thispaperestablishesthedistinctionbetweendiversityitselfandthemaineffectsofrace, gender,andage.(Duetodatalimitationsdescribedbelow,werefertothecategorieswhite, black,Asian,and Hispanicas"race,"althoughHispanicismoreaccuratelydescribedasan ethnicity.)Weuserichmeasuresofdiversityalongmultipledimensions.Importantly,we identifydiversityasanonlineareffectofemployeedemographicshares.Becauseweexamine broaddemographicspan,withstoresthathavebothfemaleandmalemajoritiesaswellasstores withbothwhiteandnonwhitemajorities,wecanidentifydiversityeffectsdistinctfromthemain demographiceffects.

Toexamineemployee -customermatching ,weuseCensusdataonthedemographicsof thecommunity(thatis,potentialcustomers).Becauseweoftenhavemultipleworkplacesinone community,wearealsoabletocontrolforthefixedfeaturesofacommunity.Weseparately analyzeHispanicsandA sianswhospeakEnglishversusthosewhodonot,asemployee -customersimilaritycanbemoreimportantwhenlanguageisapotentialbarrier.

Ourgoalhereistoshowhowsalesareaffectedbyworkplacediversityandbythe demographicmatchbetweenworkpla ceandcommunity.

# **Theory**

Wefirstdiscusstheoriesthatexaminewhethersalesofaservicebusinessdependonthe diversityofitsemployeesbecausecustomerscareaboutthedemographicsofthosewhoserve them. Wethenturntotheoriesonhowdiversity mayaffectproductivity by affecting the internal dynamicsofthework group.

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## Employee-CustomerMatches

Mosttheoriesoftheemployee -customermatcharebasedontheimportanceofsimilarity.

Afterdiscussingthesetheories, wethen discusse veralalt ernatives.

#### **Similaritytheories**

Severalrelatedtheoriessuggestthatthematchbetweenemployeeandcustomer demographicscanimprovestoreperformance.Importantexamplesincludesocialidentitytheory (TajfelandTurner,1986),similarity -attractionth eory(Jacksonetal.,1991;Tsui,Egan,and O'Reilly,1992),social -categorizationtheory(TajfelandTurner,1986),andBecker'stheoryof customerdiscrimination(1957).Inthesetheories,familiarity,thedesiretoconsidersimilar peopleasholdingde sirabletraits,andpreferencestobenearthoseoneconsidersthe"ingroup" leadtopreferencesfordoingbusinesswithsimilarothers.

Aclosematchindemographiccharacteristicsmayalsoimproveemployees' understandingofcustomers' preferences (Jac ksonand Alvarez, 1992; Cox, 1993). Additionally, employees who are demographically similar to customers may have an easier time understanding how customer preferences change over time. Finally, some studies indicate that employees can also attract customers using connections within the community (Cox, 1993; Ibarra, 1992, 1995). That is, in many sectors (including the one we study), an employee's social ties often help bring customers to the work place and increases a lest othem.

JenniferLee(2001)hasi dentifiedtwoadditionalmotivesforstoreownerstohire employeeswhomatchcustomers'demographicsinherstudyofretailstoresinlargelyblack neighborhoods. Shehasfoundthatwhiteand Koreanshopkeepersfacedisputes (for example, about are turned item) that canquickly escalate and gain aracial tinge. Thus, storeowners inher inner-city sample prefer to have at least one blackemployee in the store to have some one who can defuse a tense situation without overtones of race. In addition, owners prefer that at least one blackemployee bevisible at all times so that customers feel the store is "giving back" to the community where it is located.

Whenemployeeandcustomerdemographicsaresimilar,communicationcostsmayfall. Jargon,slang,andsp eechpatternsallvarybydemographicgroup.EvenamongnativeEnglish speakers,racial(Lang,1986)andgender(Tannen,1990)differencesoftenmakecommunication difficult.

Theseconcernsaboutcommunicationcostsgrowinimportancewhenalargenumbero potentialcustomersdonotspeakEnglishwell.AlthoughmostimmigrantslearnEnglishrapidly (FriedmanandDiTomaso,1996),inmanycities,largeimmigrantenclavescontainasubstantial numberofpeoplewhocannotorprefernottospeakEnglish.

Thesemotivations can all leadprofit -maximizing employers to desire awork force that is demographically similar to its customers. When search is costly for customers, they lead to the hypothesis that sales are higher when the work forced emographics are simi lart ocustomer demographics, not with standing the legal risk in curred by discriminating in employment.

#### **AlternativeTheories**

ThestandardeconomicmodelofdiscriminationduetoBeckerdoesnotdistinguish betweenlikingwhitesanddislikingblacks:prefe rencesarerelativeandtheeffectsofsimilarity shouldbebroadlyproportionaltothematchofcustomersandemployees.Wegobeyondthis standardmodeltotheoreticallyandempiricallydistinguishpositivefromnegative discrimination.With"negative discrimination"customersofoneraceavoidstoreswith employeesofotherraces(nomatterhowfew).Forexample,ifnegativediscriminationagainst blacksholdstrue,employingevenasmallnumberofblackswouldreducesales.Negative discriminationis tightlylinkedtotheoriesofstatusandpower.Demographictraitssuchasrace andgenderaretacitreflectionsofstatusinorganizations(Kanter1977;Nkomo,1992;Ely, 1994).Racialandgender -basedinequitiesinorganizationsarereinforcedandjus tifiedby stereotypesandbiasesthatascribepositivecharacteristicsandthereforeahigherstatustowhites andmales(Nkomo,1992;Heilmanetal.,1989).

Incontrast, with "positive discrimination" customers are attracted to stores with at least a fewemployees of their own race (no matter how many). For example, a customer who speaks on Spanish primarily want sat least one employee to be working in the store who speaks Spanish. There are diminishing returns to having multiple Spanish - speaking sales people. When customer shave positive discrimination, stores maximize profits by having a fewemployees of every race. If these cases are common, we should see sales increasing a seach non white race's share rises above zero and then leveling of f. We test these variants below.

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## **EvidencethatCustomersPreferSimilarEmployees**

Tosumup, hypotheses drawn from a number of social science simply profit -maximizing employers may desire a work force that is demographically similar to its potential customers. In spite of the many theories supporting this idea, the evidence for this effect is generally weak, with one important exception.

For example, the literature on marketing contains sever als mall -scale studies that offer a mixture of results with no clear pat tern that sales are higher when customer and employee demographics are similar (e.g., contrast Churchill, Collins, and Strang (1975) with Dwyer, Richard, and Shepherd (1998).

Someevidencefromotherspheresindicatesthat"customers" --whenbroadlydefine din non-retailsettings --dobetterwithdemographicallysimilarserviceproviders.Onerandomized experimentindicatesthatstudentslearnmorewhenteachersareofthesamerace(Dee,2001).A nonrandomizedstudysuggestspatientsaremoreinvolvedin theircarewhentheirdoctorsareof thesamerace(Cooper -Patricketal.,1999).

Otherstudiesexamineemployee -customersimilaritybutdonotlookatactualsales performance. For example, one important study indicates that newly hired low -wageworker's who have direct contact with customers are more likely to match the demographics of those customers than are new hires who have no customer contact (Holzer and Ihlanfeldt, 1988). Similarly, employers as different as federal agencies (Borjas, 1982) and estaurants (Neumark, 1996) have been shown to hirework for cest hat approximate that of their clients. Employers here are acting as if customers discriminate.

Theevidenceforcustomerdiscriminationisstrongestforprofessionalsports. For example, studi esfindthat white players' base ball memora biliasells for more than the memora bilia of similarly accomplished black players (e.g., Andersen and La Croix, 1991; Nardinelliand Simon, 1990; and Gabriel, Johnson, and Stanton, 1999, but not 1995). In addition, white basket ball players have been shown to attract more fans than do black players of similar quality, which presumably contributes to whites' higher pay (Kahnand Sherer, 1988). Also, professional basket ball teams in cities with a high proportion of white resident stypically employahigh proportion of white players (Burdekinand Idson, 1991). In football, there is no racial wage gap, but white players earn more in cities with a high proportion of whites, and non white sear no recipies with a high proportion of non whites (Kahn, 1991).

The evidence above documents two important points. First, academic shave only little evidence, and what we have is mixed, evidence as to whether customers prefer to be served by similar other sin retail and service occupations, although the evidence is more consistent in other spheres. Second, employers often actasif customers have this preference.

Despitethelackofconsistentevidence, proponents of diversity routinely advocate that employers must hireadivers ework force to attract diverse customers. Examples can be found in tradepublications including those serving marketing departments (Bertagnoli, 2001), stock brokerages (Lee, 2000), voluntary associations (Baker, 1999), restaurants (Lieberman, 1998), realestate (Liparulo, 1998), health care providers (Chyna, 2001), and many others.

Advocating discriminatory customer preferences as a rational efor hir ing non white workers is an ironic twist in the history of American race relations. For much of the last 300 years, proponents of segregation have proposed that customers prefer to be served by similar others. The foundation of the fight against discrimination has been the proposition that individuals be treated as individuals, rather than on the basis of their membership in a demographic group. The theories are the same, but the older proponents of segregation as sumed most customers were white, while many modern proponents of diversity as sume customers are racially diverse.

## EffectsofDiversityWithintheWork place

Evenifdiversitydoesnotaffectbusinessperformancethroughcustomerpreferences,we needtoaskifitstillhasdirectproductivityeffectsbyaffectinghowemployeesworkwitheach otheringroupsorteams.Inthissection,wedocumentthatbo ththetheoryandevidenceonhow employees'similaritywitheachotheraffectsperformanceshowmixedresults.

First, theories of diversity emphasize that diversity can have both positive and negative effects. Studies indicate that diverse teams can hele pperformance because they are more likely to have the information needed to solve any given problem (Lazear, 1998), come up with more creative solutions than do homogeneous groups (Thomas and Ely, 1996; Nemeth, 1985), and are more likely to have employees within sights into the needs of customers (Thomas and Ely, 1996). At the same time, diversity can increase the costs of communication within the work force (Lang, 1986; Zengerand Lawrence, 1989), lower group cohesiveness (Pfeffer, 1983), increase

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<sup>&</sup>lt;sup>1</sup> WilliamsandO'Reilly(1998)andReskinetal.(1999) provideexcellentrecentreviewsofdemographicresearchin organizations.

employeeturnover(O'Reillyetal.,1989;Jacksonetal.,1991),andreduceincentivesfor cooperation(Greif,1993).

Giventhecontradictorytheoriesandthemixedevidencesurroundingdiversity's effects, itiscrucial to examinedirectly how diversity affect sretails to reperformance.

#### **DataandMethods**

Inthisstudyweexamineover800workplacesandover70,000employeesofasingle largeservice -sectoremployer. Totesttheeffectofemploymentdemographicsonperformance, anidealexperimentwouldrando mlyvarydemographicswhileholdingallotherpossibly confoundingfactorsfixed. Studiesofemploymentarebedeviled by unmeasured differences in policies, practices, and the working conditions across different employers. Although we do not have random demographics, we come close to achieving most of the dataneeds for a study of employee diversity and employee -customer match. In particular, our design minimizes unmeasured differences across work places.

Inmostfieldstudies, demographics are highly cor relatedwithotherfeaturesofthe workplaceorjob; for example, female -dominated occupations and establishments typically involvequitedifferenttasksthandothosedominatedbymales. Theworkplaces in our study, however, exhibital most none of this va riation. Eachwork place has minimal local discretion, as eachmustimplementthedetailedhumanresourcepoliciesdisseminatedfromcorporate headquarters. Wages, internal hierarchy, fringebenefits, jobcontent, and product and service prices, are fort hemost part centrally set and uniformly implemented. As is common among national chains that promote a common branding e, the employer has purposefully attempted to replicatethesameoutletcharacteristicsineveryU.S.marketofsignificance.Adverti sing, productselection, pricing, and human resource policies are all centrally determined to promote uniformity. The employer's goal is that customers and employees perceive work places in differentlocations as essentially interchangeable. The remaining variationisfarlessthanwould beobservedacrossmostotherjobs, employers, or industries. This standardization limits possible confounds between demographics and omitted job, product, or establishment characteristics.

Astheestablishmentsweanalyz earedispersedacrosstheUnitedStates,location -specific factorsmayaffectbothdemographicsandsales.Forexample,inner -cityestablishmentsmay

havebothlowsalesandahighpercentageofminorityemployeeswithoutanydirectcausallink.

Weuse specificationsdesignedtocapturefixedfeatures,measuredornot,oftheworkplace,
labormarket,andcustomers. Alocallabormarketshockmightaffectbothchangesin
demographicsandchangesinsales;thus,insomespecifications,weincludeacommun ityfixed
effectwhenexaminingchangesinsales.

Additionally,thisstudyunpackstheconceptofdiversityintoanumberoftheoretically andempiricallydistinctmeasures. Mostprevious studies have had nowork places with female, black, or Hispanic maj orities. The limited range of data implies that a single diversity measure conflates both a main effect (such as rising percent female) and gender diversity. The data used in this study are unique among studies of organizational demography in having as unique among studies of organizational demography in having as unique and the main effect of percent female, percent black, and percent Hispanic. While field research usually involves trading as maller number of observations for greater depth, this study examines over 800 work places. This figure is roughly the total number of natural work groups in all the field studies reviewed by Williams and O'Reilly (1998).

Againstthesevirtueswemustcountthelimitationsofthisstu dy,detailedinthe

Discussionsection.Mostimportantly,thisisacasestudyofonelargeemployerinthelow -wage
servicesector.Althoughnotrepresentativeofallemployers,thiscasestudyprovidesacleaner
studydesignwithresultsthatareplaus iblyapplicabletoalargesectoroftheU.S.workforce.

## Specification

Wefirstmodelthematchbetweenastoreandacommunity, and the nenrich themodel to account for within -storediversity. We assume that the current matchbet we enastore and its community determines the current level of sales in a store. Equation 1 presents a simple reduced-formempirical specification where sales at store incommunity c at time t depend on stored emographics ( $demog_{ict}$ ) such as the proportion Hispanic, others to eobservable characteristics ( $X_{ict}$ ), community demographics ( $demog_c$ ) such as the proportion Hispanic in the community, other community observable characteristics such as the distribution of household income ( $Z_c$ ), and time effects z (time):

1)  $S_{ict}=a+b$  otime+b  ${}_{1}X_{ict}+b$   ${}_{2}Z_{c}+b$   ${}_{3}demog$   ${}_{ict}+b$   ${}_{4}demog$   ${}_{c}+b$   ${}_{5}demog$   ${}_{ict}\cdot demog$   ${}_{c}+e$   ${}_{ict}$ 

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<sup>&</sup>lt;sup>2</sup>Wecontrolforeachsamplemonth.

Whileeachstorehasauniquecommunity, we will take advantage of the fact that many communities have multiple stores. For the theories of store -communitymatch, the coefficient of interestis b<sub>5</sub>, whichtellsusifaddingmoreHispanicstoastore(forexample)ismoreusefulin areaswithahighproportionHispanic.Forexample,if b<sub>5</sub>ispositive,thenmovingfrom3to30 percentHispanicemployeesinacommunitythatis20per centHispanicwillincreasesalesmore thanthesameshiftinemployeedemographicsinacommunitywith2percentHispanics.

Themaineffectonstoredemographics b<sub>3</sub>capturesworkercharacteristicscorrelated with race(forexample,ifwhitesattendbett erhighschoolsthannonwhites)andcharacteristicsofthe neighborhoodthatpredictwhatgroupswouldchoosetoworkinthissector(whitemenmay workinlow -wageretailmoreoftenwhenlabormarketsareweak). These areofsecondary interesthere. The maineffects also capture customer discrimination that is shared by all demographic groups. For example, in our society, all demographic groups may prefer to be servedbycertaingroups; eitherhigh -statusgroupsor(ifpeopleprefertohaveservicepeop lefit stereotypes)bylow -statusgroups.Becausethemaineffectsonmeanage,raceandgender conflatetheseseveralforces, the coefficients on the main effects are open to a variety of interpretations.

One problem with estimating equation (1) is that theresidual  $e_{ict}$ isprobablycorrelated withunobservablefeaturesofthestoreandcommunity. Specifically, assume the residual includesunmeasuredstorecharacteristicsthatarefixed(  $u_i$ ), unmeasured community characteristicsthatarefixed  $(v_c)$ , as wellasawhitenoiseresidual  $\varepsilon_{ict}$ :

(2) 
$$e_{ict} = u_i + v_c + \varepsilon_{ict}.$$

Ifthepersistent butun observed determinants of a store's characteristics  $v_c$  are correlated withbothsalesandemployeedemographics, the nest imates of the employeedemographic coefficientsinequation(1)willbebiased.Forexample,ifblacksworkinareaswithlow incomes(beyondtheeffectabsorbedbyourdirectcontrolsforcommunityincome),thenthelow incomes.notrace.couldreducesales.

<sup>&</sup>lt;sup>3</sup>Asnotedbelow,resultsusingtheabsolutevalueofthegapinstoreandcommunitydemographicsresemblethose intheinteractionspecificati on(1). This absolute value of the gap is more sensitive to misme a surement of the appropriate community and racial boundaries than the interaction we use.

To the extent that the factors affect in gboth demographics and sales are fixed, we can first difference equation (1) to eliminate the omitted store and community characteristics ( $u_i$  and  $v_c$ ):

3) 
$$\Delta S_{ict} = b_0' + b_1' \Delta X_{ict} + b_3' \Delta demog_{ict} + b_5' \Delta demog_{ict} \cdot demog_c + \Delta \varepsilon_{ict}.$$

Firstdifferencingalsoeliminatesallfixedobservablefactorsconcerningt hestoresand communities ( $Z_c$  and  $demog_c$ ).

The first difference estimator in (3) analyzes only aportion of the variance contained in the pooled time -series cross -section regression (1). That is, the cost of eliminating omitted factors ( $u_i$  and  $v_c$ ) is that we throw out most variation in stored emographics. To balance this, we also examine the between -store component that averages each store 's sales and characteristics over the sample period:

4) 
$$S_{ic} = a'' + b_1'' X_{ic} + b_2'' Z_c + b_3'' demog_{ic} + b_4'' demog_c + b_5'' demog_{ic} \cdot demog_c + e_{ic}''$$

Compared with the first - difference es timator (3), this estimator captures more of the long - term relations between community and stored emographics and stores ales. Given that preferences a cross these specifications depend on a complex balance of judgments, we will present both the pooled specification and its components, the within and between specifications, and a formal test of the fixed effects model.

Apossible problem with eventhe first - difference specification in equation (3) is that the omitted community factors may not be fixed over time. In the worst case, they change over time while affecting both work placed emographics and sales. For example, astorethat is experiencing a positive demands hock may hir efrom demographic groups that it normally avoids. In this case, we could be spuriously attributing the effect of other evolving factors to demographics, biasing the coefficient estimates. Equation (5) presents the residual sinthis case:

5) 
$$e_{ict} = u_i + v_{ct} + \varepsilon_{ict}.$$

Anyremainingomittedvariablebiasduetolocalshockscanber esolvedbyadding detailedlocation -specifictime\*placeinteractions,exploitingthefactthatmanycommunities, indeedmanyZIPcodeshavemultiplestores. This specification corresponds to including separateintercept for each ZIPcode in the first differences version of a two period panel:

6) 
$$\Delta S_{ict} = b_0 + b_1 \Delta X_{ict} + b_3 \Delta demog_{ict} + b_5 \Delta demog_{ict} \cdot demog_c + ZIP_c + \Delta e_{ict}.$$

The resulting estimates of the interaction term  $b_5$  can be thought of as answering the following question: Consider increasing the proportion Hispanicin one store in a community but

notinanearbystore. Willthat addition increase relatives ales of the increasingly Hispanic store more if it takes place in a highly Hispanic region of the Southwest than if it takes place in a low Hispanic portion of the Great Plains?

Thestrengthoft hisestimatoristhatwehavedifferencedoutbothfixed -store characteristicsandcommunity -levelshocksthatmightaffectbothstoredemographicsandsales. The costist hat double differencing removes most of the variation in sales and indemographics, so precision declines.

Theestimatesthatusetimeseriesvariationwillhaveautocorrelatederrorsinthehistory of each store. We correct standarderrors for first - order autocorrelation using the Prais - Winsten correction.

Inaddition, weadd measur esofthelevel (equations 1 and 4) or change (equations 3 and 6) of workplaced iversity to each equation to study the effects of changes inhowemployees resemble each other.

Animportantquestioniswhatsourcesofvariationremainafterallofthisdif ferencing.

Theseworkplaceshireroughlythreeentireworkforcesayear,asisstandardinentry -leveljobs.

Thus,naturalfluctuationsinwhowalksinthedoorwillprovidesubstantialvariationin

employmentthatisreasonablyexogenoustosales.(Inr elatedresearchweexamineinmore depthhowtheraceofmanagersaffectsthehiringandretentionofworkersofdifferentraces [xx].)

Finally, because of the strong advantage that may arise from speaking a foreign language whencustomersdonotspeakEn glish, wetestwhether the presence of Hispanice mployees predictshighersaleswhenmanynearbyresidentsspeakSpanishbutnotEnglish, whileAsian employeespredictshighersaleswhenmanynearbyresidentsspeakAsian -Pacificlanguagesbut notEnglish. Thistestisastraightforwardextensionoftheabovemodelsaugmentedwiththe shareofHispanicemployeesinteractedwiththeshareofnearbyresidentswhospeakSpanishbut notEnglishandtheshareofAsianemployeesinteractedwiththeshareofresid entswhospeak Asian-PacificlanguagesbutnotEnglish(aswellasmaineffectsforeachshare).Ourestimates willunderstatethebenefitsofemployeeswhospeakthelanguageoflinguisticallyisolated customerstotheextentemployeeswhoself -identify asHispanicdonotspeakSpanish. Moreover, even Asian employees who speak an Asian language may not speak the language of allnon- English-speakingimmigrantsfromAsiawholiveinthestore's community.

## **TheSetting**

Theemployerisinanindustrycharac terizedbynumeroussmalloutletsthatsell somewhatdifferentiatedproducts. Eachworkplacewestudyiscompanyowned and typically employs 15to 40 part - time employees with several full - time managers and assistant managers. Because employees workscatt eredshifts through the week, they work with a changing mix of the other employees. Most front line employees rotate through these veral tasks in the store, spending some of their time dealing with customers and other time in support tasks.

Nonmanagerial employeesreceiveminimaltrainingwhentheyarehired. These employeesinteractwitheachothertomaintainstockandservicecustomers, butthese interactionsarenotcomplex. The Taylorist production techniques, with highly centralized decision making and limited local discretion, may well limit the potential impact of any employee differences on productivity. Further enhancing the likelihood that diversity effects will be muted managers receives ometraining in managing a diverse work force.

The employer hiresa diverse work force. This employment patternarises partly because the employer has a reputation for gender and race diversity in its marketing and employment. In addition, in our interviews, managers noted that they hire many employees from a mongther anks of customers. A diverse customer baseleads naturally to, but does not fully determine, a diverse work place.

#### Data

We combine employee -level data on demographics, store -level data on sales, and data from the 1990 Census on community charact eristics. The employee data are the complete personnel records from February 1996 to October 1998 on over. We analyzed at a on front line work place employees, dropping work places with fewer than tenemployees. We organize the data into store -month observations.

We complement our quantitative analysis with semistructure dinterviews of roughly a dozenem ployees and a half - dozen managers at work places scattered across one region of the country. These interviews were neither random no rare presentative samp le, but they do help fleshout the statistical analyses.

#### Store-LevelVariables

Thedependentvariableisthenaturallogarithmofrealmonthlysales.Inourfirstsetof specifications, weanalyzedatapooledacrossstoresovertime. Wethenlookonlyat variation between stores, averaging each store's sales overall available store -months. We next analyze variation within the history of each store, looking at year -on-year differences in monthly sales. Finally, we add ZIP code fixed effects to the regres sions on sales growth.

Fromthecompany'shumanresourcedatabase, we construct astore -month dataset of employeed emographics, including the proportion female, average age, and the share soft hree categories for race or ethnicity (black, Asian, and Hispa nic, with white, the small percentage Native American, and unknown ethnicity categories pooled as the baseline). The race and ethnicity codes are the company's coding, and they create a set of mutually exclusive and collectively exhaustive categories that for simplicity we refer to as "race." Educational requirements are minimal, and educational attainment varies little. Fewemployees have a college degree. Additionally, the employer imposes few hiring prerequisites.

We control for a racteristics when we analyze between -store variation; control sinclude the logarithm of employment, store age and its square, time since the last store remodel and its square, store size (measured in square feet) and its square, and indicator variables for if the store is on the street, a commercial strip, or in a mall.

Salesperstorewillalsodependonthenumberofnearbycompetitors. We controlfor the numberofestablishments that are in the same county in the same four -digit industry as reported in the 1998 County Business Patterns. To control for other local factors, some estimates include an extensive set of dummy variables, one for each ZIP code with more than one store.

#### **CommunityVariables**

Toconstructcommunitydemographics, weuseeachstor e's ZIP code to identify azone of "nearby" Censustracts, defined as those in its ZIP code or within two miles of the centroid of its ZIP code. We then merge 1990 Census data for this zone to each store.

Weconstructtheproportionblack, Hispanic, Asian , and female surrounding each store, as well as the age distribution in the surrounding community using the following data. The 1990 Census as k squestions on race (black vs. white, etc.) separately from ethnicity (Hispanic vs. non Hispanic). Thus, on the Census, respondents can categorize themselves as both black and

HispanicorasbothwhiteandHispanic.Incontrast,theemployerhasmutuallyexclusivecodes ofwhite,black,andHispanic(aswellasAsian).WeallowboththeCensuscategoriesof populationandtheemployer'scategoriesofemploymenttoenterunrestrictedinourequations.

Wecontrolforseveralothercommunitycharacteristicslikelytoaffectproductdemand.

Ascontrolvariables, weuse Census data on the household income distributi on (percentages of household sine achoften detailed income categories), the age distribution (percentages of individual sine achofs ix age categories), total population within two miles categorized into six size groups, and the unemployment rate. Because population is measured within a fixed two -mileradius, it can be thought of a sapopulation -density measure. The income figures are only available for the store's ZIP code, without the two -mileradius of surrounding tracts.

## **Store-CommunityInteractions**

Formatchingtheories, the variables of interestare the interaction between store and community demographics. Such interactions allow us to test, for example, for the effect of having a highly Hispanic work for cenear a Hispanic population center. The racial composition of the stores are highly correlated with the composition of the community (for example, the white shares are correlated at 0.70); nevertheless, substantial variation remains a cross stores. In addition, ther a cial shares vary substantially over time as well.

Wealsomeasuretheinteractionbetweentheproportionfemaleatthestoreandinthe community. Aside from some areas containing military bases, single -sex colleges, and mining operations, there is much less variationing enders har est han in race or ethnicity across locations. Thus, we have little testable variation in the proportion of females across communities.

#### **DiversityWithintheStore**

We calculate age, gender, and racial diversity within the store as well as the surrounding community. For race and gender, we use a diversity index equal to the odds that two peoples selected a transformation are reasonable to the state of the state of

Diversityindexonraceorgender=  $l - \sum_{i} S_{i}^{2}$ ,

where  $S_i$  is the share of each gender or racial group i. This diversity index is zero with complete homogeneity and is maximized when each group has an equal share of employment. Economists might naturally think of it as one minus the Herfin dahl Index.

Mostpastresearchershaveusedthecoefficientofvariationonageorthestandard deviationofagetomeasureagediversity. Weprefertousethestandarddeviationwithinthe workgroupofthenaturallogarithmofage. The standarddeviat ionoflog(age)implies that proportional gapsinage are what lead to social distance; for example, the age gap between 18 and 22 usually leads to more social difference than does the age gap of 40 to 44, although the two gaps are the same in absolute years. As with the race and gender diversity in dices, the standard deviation of log(age) has a simple interpretation: It is approximately the expected percentage gap in the age of two people chosen a transform. This relation holds exactly for normally distributed variables.

#### Results

## SummaryStatistics

SummarystatisticsarelistedinTable1. Themeanageofemployeesinourdataisonly 24 years. Asthisisnotasectororafirminwhichmostemployeesstaytobuildacareer, most employeesfallwithina fairlynarrowrangeofages. Themeanofthewithin -storestandard deviation of the logarithmofages is only 27 percent.

Weobservevaluesofthegenderdiversityindexinoursamplecoveringthefullpossible rangefromzero(allfemale)toone -half( anevenmixofmenandwomen),withameanof.34. Anincreaseingenderdiversityisnotthesameasanincreasingproportionofwomen. The proportionofwomeninthestoresrangesfrom6percentto100percentwithameanof75 percent. Theracialdiv ersityindexrangesfromzeroto.79, withameanof.39. These are entry leveljobs; thus, the stores are more black, more Hispanic, more Asian, more female, and youngerthan their communities.

#### PooledTime -SeriesCross -Section

Salesdependonthecommu nity'sracialandgendercomposition, even after controlling for the community's income, unemployment, and population density (Table 2 column 1). Sales are significantly higher incommunities with agreater female populations have and allower black populations have. Recall that female share varies very little; it is unclear whether this coefficient has any economic significance. It is important to remember that these results condition on the firm's decision of how to market and where to open stores. (Few stores close in our sample period.) Either the company has not completely succeeded in marketing to a diverse customer base, or its choice of locations has not equalized sales on the marginacross stores. The impact on profits depends on the extent to which these sales differences are offset by storerents.

Astore's ageandracedistributionsalsohelppredictsales. Salesaresignificantlylower instoreswithgreaterproportionsofblackemployees. Underdepressedeconomic conditions, whitementend tobumpdownintothissector, which works against finding negative effects for both female and minority employees. The black result is consistent with customer discrimination. A 10 percentage point increase in black employments have (at the expense of the baseline group of whites) is associated with. 8 percent lowers ales. The same increase in Asian employments have is associated with. 6 percent greaters ales. The Hispanic employments have does not significantly predict which stores have high sales. The work force's average age predicts slightly highers ales, are sult consistent with the theory of general human capital. Many of these results are sensitive to the alternative specifications discussed below.

## **Store-CommunityInteractions**

Thestore -commutiyinteractionsarepresentedinTable2,column2;thisspecification correspondstoequation(1).Inresultsnotshown,wefind(asexpected)thatstoreracial compositionlargelyreflectsthedemographicsofthecommunity.Nevertheless,s toresdono t simplymatchtheircommunitiesandthereremainstestablevariationinstoredemographics beyondcommunitydemographics.

This column presents the first main result of the paper: Does matching a community is race increases ales? The coefficients on the interaction of store and community race are mixed, providing no consistent support for the ories of customer preference. Specifically, the coefficient on (Store % Asian) \* (Community % Asian) is a small negative number (contrary to theory), while

theinteract ionsonblackandHispanicaresmallandpositive;nonearestatisticallysignificant. As noted below, the signs of these interactions are not stable across specifications.

Unlikerace, the proportion female is similar in almost every community in the Un States. To avoid extreme multicollinearity, we use the gap between store and community percent female (instead of their interaction) and contrast stores in the top and bottom quartile of this distribution with those in the middle. Stores in the bott om quartile of store percent female minus community percent female have 1.2 percent highers alest hans to resint he middle two quartiles. Working against the importance of this result is that stores with the top quartile of store percent female minus community percent female) have 0.3 percent highers a lest hans to resint he middle two quartiles.

Theimportantfindinghereisthatweseeneithersignificantnorsubstantialevidencethat matchingemploymentsharestopopulationsharesinthesurroundingco mmunitymattersfor sales.

## **PositiveandNegativeCustomerDiscrimination**

Theresultsincolumn1ofTable2includedonlyamaineffectontheshareofeachracial groupinthestore.Incolumn2weaddinquadraticterms,whichpermittestsofpositive versus negativecustomerdiscrimination.Resultsdifferacrosstheracialgroups.

Whenwelookatthesquaredtermsonthemaineffectsofrace,employingHispanicsis usefulintherelevantrangebutatadecliningrate.Inotherwords,astore'ssales arehigherifit employsatleastafewHispanics,aspredictedbyourtheoryofpositivediscrimination.

Thereceptionofblacksdiffers.Incolumn2ofTable2,thefirst -ordertermonthe proportionblackinthestoreisinsignificantlynegativewhile thesquaredtermissignificantly negative.Thecombinationoftheseresultssuggeststhatthefirstfewblacksinastorehavelittle effectonsales,butthatbeyondthatlowthreshold,salesdeclinewiththeproportionblack.

Omittedproductivitychara cteristics(forexample,thatblacksattendworseschools),could accountforalineareffect.Buttheacceleratingdeclineinsalesasblackemploymentshare increasessuggestsnegativecustomerdiscrimination —manycustomersavoidstoreswithblacks.

## **DiversityWithintheStore**

Employeediversityoftenmatters, butinwaysthatarecomplex. Evenwhere the effect of diversityons alesis statistically significant, it is often modest in magnitude. The small magnitude of most of these effects is our second major result.

Diversityisidentifiedasanon -lineareffectofchangingdemographicemployment shares. When we add the storediversity measures (Table 2, column 3), age diversity is bad for sales, gender diversity is in significant, and racial diversity is weakly positive. Given that most stores have a white majority, increasing racial diversity implies increasing the share of Asians, blacks, and Hispanics. When we include the negative main effects of each nonwhite race on sale stocal culate the total derivative, we find that over most of the relevant range, the total effect of increasing diversity is small, negative, and not statistically significantly. In contrast, the estimate deffect of age diversity is important; increasing our measure of age diversity by a standard deviation (that is, moving from a standard deviation of log (age) of .27 to .33) lowers sales by 15 percent.

Whenwecombinethestore -communityinteractions with the within -storediversity measures, results remain similar (results ava ilable on request).

#### Between-StoreResults

Mostofthemainresultsfromthepooledanalysesreappearwhenweignoretime -series variation(thefocusofthenextsection)andlooksolelyatbetween -storeaverages. Theresults in Table 2, column 4, corre spondwith equation (4). Column 5 shows results with diversity indices. Gender diversity and matching a community's race or gender composition have no statistically significant effectors ales. As in the pooled specification, age diversity again predicts lower sales; the effect is even larger in the cross -section. Racial diversity helps sales, an effect that is both stronger and more significant in the cross -section than in the pooled specification. These results control for differences a cross community in income, unemployment, population density, and retails to redensity.

The positive coefficient on racial diversity implies that diversity predicts highers ales, holding all else constant. While we can statistically identify diversity as a nonlinear effect of distinct from the main effects, at least two of the racial shares must change to change racial diversity. Thus, the total effect of changing the racial composition of a store to move from an

all whitestoretoonewithamixtureclosetothenationalav erage(70percentwhite,10percent eachofblack,Hispanic,andAsian)wouldraisepredictedsalesby4.2percent.(Thisis statisticallyinsignificantevenatthe10percentlevel.)Movingfromthatmediumleveltoa highlydiversestore(40percentwhi te,10percenteachofblack,Hispanic,andAsian)would lowerpredictedsalesby2.5%;again,thepredictedchangeisnotsignificant.

## Within-Store Year -on-Year Changes

Thepooledandbetween -storeregressionsarebothsubjecttoomittedvariablebiasdu eto unmeasuredfactorsinalocationthataffectbothsalesanddemographics. Althoughwecontrol forincome, unemployment, populationdensity, retaildensity, and other community factors, a Hausmanteststronglysupports the importance of store fixed effects. The Hausmantest examines if the coefficients on store characteristics are stable when we shift from random to fixed effects; the coefficients differ significiantly, suggesting that fixed effects is more appropriate.

 $The results in Table 3 are bas \qquad edon a specification that difference soutther emaining \\ omitted unchanging factors, a sine quation (3). We estimate the regressions using year \\ -on-year \\ changes in log sales in column 1.$ 

Asnotedabove, eventhese specifications are subject to concerns about omitted local shocks that affect boths ale sand demographics. For example, consider two stores in the same neighborhood. What ever omitted for cest hat affect product demand or demographic supply in one such store are likely to affect the other store as well. We isolate from the sedemand or supply shocks common to such "brother" stores.

Incolumns3and4weaddcontrolsforcommunityfixedeffectsbasedonZIPcodes,as inequation(6). Thus, two levels of differencing are applied: differencing within stores across time and comparing across stores sharing a ZIPcode. This specification answers the question of whether when one store in a community moves to better match the community demographics, does its sales increase relative to an earby storet hat does not adjust its demographics. This is a desirable "brothers" specification that fully exploits the richness of the data. For example, the location fixed effects fully capture any regional change in community in come, taste, or demographics.

4

<sup>&</sup>lt;sup>4</sup>Similarresultsarefoundcomparingmonths, quartersory earson eyear apart.

Theco stofthismorerigorousprocedureisthatitreducesthenumberofstoresand ignoresallvariationinsalesthatispersistentacrossmallsorcommunities. When werunthe regression on the rate of change of sales, the Hausmantest strongly supports the importance of the ZIP code fixed effects.

#### **Store-CommunityInteraction**

Wefirstexaminetheeffectsofstore -communityinteractions.Inbothspecifications, as withthepooledresults, perhapsthemostinteresting finding is how few of the coefficients are large or statistically significant. That several statistically significant results in the cross -section (Table 2, especially column 5) are not present in the time series follows from less testable variation in the time -series, but may also suggestom ted variable bias in the cross -section despite the community controls.

Increasing the % Asian has no effect on sales in most communities, but the effect is negative in highly Asian communities (col.1). The reduction in benefit in highly Asian communities remains but loses statistical significance with ZIP code fixed effects (col.2).

Incontrast, raising astore's % black reduces sales slightly in highly black communities, but only when controlling for the ZIP code fixed effects (col.3). This results u ggests that the patterns we observe are not simply due to potential white customers discriminating against blacks. Incommunities with few blacks, incontrast, increasing the store's blacks have has a modest but in significant positive effect on sales.

## **DiversityWithintheStore**

Whenweturntotheeffectsofdiversitywithinastore,resultsaresimilartothepooled estimates. Growing agediversity predicts lowers ales growth. Aonest and ard deviation in the dispersion of logage (almost 5 percent, so that two workerpicked at random are about a year further apartinage) reduces a les growth by slightly less than. 5 percentincol. 1, and slightly more than. 5 percentincol umn 3 (with ZIP code fixed effects).

Theeffectsofrisingracialdiversitya realsostatisticallysignificantandnegative;in contrast,racialdiversityhadapositiveeffectinthepooledandbetween -storeregressions.As always,wemustconsideramoveinracialdiversityintermsoftheunderlyingshiftsinracial employment shares.Forexample,amovefromanall -whitestoretoroughlytheretailchain

average(70% whiteand10% each other group) predicts 1.3 percent lowers ales (change is now statistically significant at the 1 percent level). If we continue to increase diversity and examine the shift from a moderate to a highly diverses to re(40% white, 20% each other group) sales remain unchanged (the point estimate is a tiny and not statistically significant -.3 percent). Because of the positive main effection % Asian and the negative main effection percent black, this result varies depending on the precise mix of workers that changes to create any given shift in overall diversity. As noted above, the semain effects could be due to customer preferences for the race of the irservice people, or to differences in human capital, among other explanations. In contrast to race, change singender diversity do not predict changes in sales.

## **ImmigrantEnclaves**

Ouranalysesoftheimportanceofhiringstaffwhoarelikelytospeak thelanguageof nearbynon -EnglishspeakersarepresentedinTable4. Theorderofthecolumnsfollowsthe orderoftheprevioustables: randomeffects on all stores; between stores; within stores, and first differences of stores including ZIP code fixed effects. Our maintest is to see if additional Hispanicor Asian employees are particularly valuable incommunities with near by enclaves of Hispanicor Asian immigrants who do not speak English.

Column1presentsthepooledtimeseries,cross -sectionalr esults(withrandomeffectsfor stores). StoreswithmoreAsianemployeeshavehighersalesifthecommunityhasmanyAsian immigrantswhodonotspeakEnglish. RecallthatmanyAsiansintheUnitedStatesspeakonly English, andthosewhospeakanAsian languagespeakavarietyofthem. Wecannotdistinguish thelanguageskillsofemployees. BecausewethennecessarilygrouptogetherAsianemployees ofvaryinglanguagesandfluency, theeffectofhiringanemployeewhospeaksthelanguageof theenclav eispresumablylargerthantheestimatereportedhere. (Totheextentmanagerslook foremployeeswhospeakthelanguageofpotentialcustomers, Asianemployeesataworkplace nearanimmigrantenclavemaybemorelikelytospeaktherelevantlanguage.

Tounderstandthemagnitudeofthecoefficientof7.1ontheinteractionoftheshareof thestore'spercentAsianandthecommunity'spercentspeakinganAsian -Pacificlanguagebut notEnglish,considertwocommunitiesthatdifferbytenpercentagepoints ontheshareof linguisticallyisolatedAsians.Thiscoefficientimpliesthatastorewitha10percentpointgreater Asianemployeesharehas7.1percenthighersalesinthecommunitywithmorelinguistically

isolatedAsiansthaninthecommunitywithf ewer.Thiseffectisbotheconomically and statistically significant across specifications.

Whenwelookbetweenstores(column2), the interaction for Asians rises in size.

Examining a complementary cutof the data, when we look within stores (column 3), the point estimates on having a rising proportion of the store's work force who share the background of the linguistically isolated remain statistically significant.

Finally, we also run the within -storeregression with ZIP code fixed effects. The coefficient on the interaction for Asians drops in size but remains statistically significant. The effect of Hispanics remains statistically insignificant, but the confidence interval includes the possibility of economically important benefits to hir ing Hispanics who do not speak English.

#### RobustnessChecks

Wehaverunalargenumberofrobustnesschecks. In all cases, results are consistent with the results presented above, with most store - community interactions small and insignificant other than results concerning linguistically isolated customers. We first discuss robustness checks for store-community interactions, then for employment diversity.

#### **Store-CommunityInteractions**

Wetestifwithin -storeracialdiversityis mostusefulinracially diverse communities. This interaction is neither large nor statistically significant.

Storereputationmightlagchangesinemploymentdemographics. Asacheck, in the pooled and within -storeregressions, we use stored emographics that are lagged amonth or that are the average of the last year. In case reputations take along time to change, we look at two year changes in sales as a function of two -year changes in stored emographics and their interaction with community demographic s. In case reputations are less important instores with unstabled emographics, we check if matching the community matters more instores with stable demographics. The store -community interactions neither increase in size norgain statistical significance.

Year-on-yearchangesinmonthlystoredemographicsmayamplifytheimportanceof transitoryfluctuationsindemographics.Weaveragesalesanddemographicsover3 -month

periodsandanalyzedyear -on-yearchangesinquarterlystoredemographicsandsale s.Results are similar to those reported in the text.

Somestoresareinneighborhoodsthatattractmanyshopperswhoarenotfromthe community. Weuseseveralmeanstoidentifysuchstoresandreruntheanalysesdroppingstores likelytoserveabroad ercustomerbase. Resultsremainunchanged.

Totestwhetherthefunctionalformschosenmightbedrivingtheresults, weperforma simplenonparametric test, looking at how stores ales grow when the proportion black at the store rises as a function of the proportion black in the community. The results shown o interaction. We repeat this exercise for the other racial and ethnic groups with similar lack of results.

Wealsoreplacetheinteractionsofstoreandcommunityraceshareswiththeabsolute valueofthegapinstoreandcommunitydemographics.Resultsremainsimilar.Becausethe storesaretypicallylesswhitethantheircommunities,andbecausetheabsolutevalueofthegap ismoresensitivetomismeasurementofdemographics,westressthespe cificationswiththe store-communityinteractions.

Wearealsointerestedinwhethersomeracialorethnicgroupsavoidspecificother groups; forexample, if all nonblack groups avoids to reswith blacks. This hypothesis is motivated by several observations; for example, Asians, Hispanics, and non - Hispanic whites intermarry among each other more often than any group does with non - Hispanic blacks. Turning to another sphere, Asians are more likely to live in racially integrated neighborhoods than are other groups. We replace the interaction of the percent black in the store times percent black in the community with the three interactions of percent black in the store with percent white, Asian, and Hispanic in the community. We perform similar substitution sfortheother groups (percent Asian in the store times percent black in the community and so forth). Overall, results are rarely precisely estimated and shown ostrong patterns.

Fortheregressions analyzing linguistically isolated potential customers, we examine the effect of Asian and of Hispanice mployees in communities with at least 1 percent and then again in communities with at least 5 percent linguistically isolated Asian or Spanish speakers. Results are consistent with the interactions presente din Table 4 in that minority employees are particularly useful in the communities where customers are most likely to need the employees' languages kills.

Wewereinterestedinwhethermanager -communitysimilarityincreasedsales. The hypotheseshereare identicaltothoseforworker -communitysimilarity. Theresultswere similarlyunsupportiveoverall, withoneexception. The single results upportive of manager communitysimilarityincreasing salesis that when comparing a cross stores, stores with black managershadhighers ales when in highly black communities than in other communities. At the same time, using the more convincing longitudinal variation, storest hat gained a black manager had slower growth when the store was in a highly black community than in a less black community. Similarly, when controlling for ZIP code fixed effects, when a stores witch estoa Hispanic manager, sales decline in highly Hispanic communities. Other manager races interactions are negative but not significant.

Inshort ,wetriedalargenumberofvariationsandfoundnoconsistentevidencethat havingworkersormanagerswhoresembledtheircommunityaffectedsales.

## **DiversityWithintheStore**

Ourmostrobustresultconcerningdiversitywithinthestoreisthecostof agediversity. Wereplacemeanageandthestandarddeviationoflogagewiththesharesofemployeeswhoare teenagers, 20 - 22, 23 - 26, 27 - 33, and over 33. Compared to those 20 - 22, teens are less productive, while the older employees are slightly more productive, with the precise pattern depending on whether we usevariation between storesor look at changes over time. However, when we control for both age diversity (the standard deviation of the log of age) and the proportion of the store under 20 or the proportion over 33, the age diversity measure remains strongly and statistically significantly negative, while the ages have sare small and statistically in significant. This results uggests that the negative effects of age diversity that we find results from something more than the lower productivity of teens or of employees who remain in this sector longer than most.

#### **TheLocusofDiscrimination**

Opinionsurveyshavefordecadesattemptedtomeasuretheextentandlocusof discriminatoryattitudesinthe US.Inrecentdecades,fewwilladmittoholdingsuchbeliefs. Whilethisisencouraging,onewonderswhethertheactionsmatchthestatedattitudes,orrather whethermanyhavelearnedthatitisnolongersociallyacceptabletostatesuchbeliefs. The storeswestudyaresopervasiveandsouniformthatwecanusethemasaprobeof

discrimination.Ratherthanaskaboutprofessedattitudes, weexamineactions, using stores as uniform testin strument. Weask whether sales in different situations are affected differently by employeed emographics. We compare stores in communities with high and low black representation, and do the same for communities with high or low populations have sof Asians, Hispanics, Females, and young. We also compare rich and poor communities classified by medianhouse hold in come, large and small cities classified by population density within 2 miles of each store, and large and small stores classified by square feet. In each case we compare the demographic effects on sales am ong store sinthe first quartile of each distribution to the effects found among store sinthe last quartile of each distribution. We also compare effects in the North to those in the Southern States. The results discussed in this section are based on consections pecifications and are rarely significant in the time - series dimension.

Thetheoriesinvolvedareoftwosorts. Acrosscommunities of different demographics, the question is whether more heavily Asian, Black, Hispanic, or female communities how different patterns of discrimination in an ation more complex than the traditional black - white dichotomy. Comparing young toold communities captures both life - cycle and historical changes.

The comparisons across city size test avery different theor youncerning search costs and the difference between thin and thick markets. Simply put, densely populated communities of fer greater choice among retailest ablishments. Diversity across establishments - each one of which might be perfectly segregated - can substitute for diversity within establishment. At the other extreme, consider the general store in a small village: little choice of establishment, but broad scope within. We compare small and large communities to test whether diversity within a store is more important within smaller communities with less retail choice.

Thereissomeevidencetosuggestitis. Tosavespace, wedonot present tables. Incross section estimates of our standard specifications, racial diversity has a significantly more positive effect on stores ales in small than in large communities. The thicker markets in larger cities allow for more specialized stores, including those with more homogeneous staffs, to find sufficient customers. Customers with a preference for staffo faparticular race can find them by searching a cross rather than within store. The implication of more racial segregation across stores in big cities than in small is, however, not strongly bornout in the data. The test is not straightforward, since it depends on non-robust case-control methods that search for small cities

withthepopulationdiversityfoundinbigcities, and in bigcities selects smaller stores that mirror stores ize in smaller cities. While the prediction of more segregation in bigger cities may seema paradoxical result to those who think of bigger cities as more sophisticated, perhaps less discriminatory, and inherently more diverse, the result follows directly from classice conomic models in which bigger markets allow greaters pec ialization. Our result parallels a similar finding for radio stations (Waldfogel, 2001).

Inbiggercities, blackemployees have a more adverse impactons ales, while Asians have a more positive impact. Similarly, racial diversity improvessales in small stores but not in big. Since in this company, big stores are found in big cities, this result may reflect the same model at work. A distinct theory for different effects between small and large stores is statistical. These work forces turnover 3 or 4 tim esayear. If customers are looking for demographic matches, past storedemographics are an oisier measure of current demographics at small than at large stores because of the law of large numbers. In stead, we see that the negative effect of blacksons all esis greater at small stores.

Athirdstratificationisbetweenrichandpoorcommunities. Becausewemeasureboth populationandmedianincomeswithintwo -milecircles, and because population density and incomes are positively correlated, this may agai npartially reflect city size effects. The adverse impacts of females and blacks on sales are significantly less in richthan in poorcommunities. Perhapstherichare more tolerant concerning those whose rvethem.

Thenegative impact of blacks on sale sisfound in large cities, not in small, and the difference is significant. In addition to the theories examined above, this result is also consistent with suburbanblacks differing from urbanblacks in ways that white sare more comfortable with. While plausible, note that the adverse impact of females on sales is also worse in big cities suggesting other forces at work.

WhileracialdiscourseintheUSisdominatedbythecategoriesofBlackandwhite,the spectrumofracerelationsismorecomplex.W efindthatHispanicemployeeshaveinsignificant effectsinbothhighandlowHispaniccommunities -withoutcontrollingforthepotentialbarriers oflanguage.BlackemployeeshaveabettereffectonsalesinheavilyHispaniccommunities.

Butthereve rsedoesnothold.Hispanicemployeeshaveabettereffectonsalesinnon -Black communities.Inotherwords,itappearsthatHispaniccustomerstolerateBlacksalespeoplemore thanBlackcustomerstolerateHispanicsalespeople.Asianemployeeshaveab etterimpacton

salesinheavilyAsiancommunities,buthavelittlesignificanteffectelsewhere.Femaleshavea positiveimpactonsalesincommunitieswithfewteenagers.Perhapstheoldarelessbashful aboutwhohelpsthem.Oldercommunitiesarealso lesssensitivetoBlackemployees. Interpretedasahistoricaleffect,thisisnotpromisingbecauseitsuggestsmorerecentcohorts discriminatemore.However,wecannotempiricallydistinguishthisfromthemoreoptimistic interpretationthatdiscrimi nationfadeswithageandexperience.Thenegativeeffectsofage diversityarealsoworseinyoungercommunities.

Despite the perception left by the Civil War and Reconstruction, the Southhashada longer experience of confronting racial division. Wef indthat Blackshave an egative impacton sales only in Northern states. In the South, the effect is in significant.

## **Discussion**

Anystudyofhowdiversityaffectsworkplaceperformancefacesanumberofchallenges. First, because of potential legal challenges, it is rarethat diversity and performance data at the company level see the light of day. Second, diversity exists as a conceptal on ginfinite dimensions. We focus here on the socially salient dimensions of race, ethnicity, gender, and age, although many other dimensions are expected to matter. Third, in practice diversity is often confused with the main effects of demographic differences. Finally, the effects of diversity are often confounded with other differences across jobs, employers, or communities.

Becausewomen, blacks, and other minority groups typically work in different places and jobsthandowhitemen, the challenge is to isolate the effects of diversity from the effects of both omitted location and occupation characteristics. We em ploy a study design that dramatically reduces this problem by using data from a single employer with more than 800 establishments. Just as an atural scientist would want to replicate conditions other than the experimental variable, the employer in this case promotes a consistent national brand and strives to hold fixed both human resource practices and the customer's experience across locations. This creates by design a nunusual degree of homogeneity across locations.

Diversitystudiescanmistakenotjus temployerdifferencesbutalsocommunity differencesfordiversityeffects. Insome specifications, weaddextensive controls for community characteristics that might affects ales. Inother specifications, we completely control for all unchanging storea ndcommunity characteristics by examining changes in sales.

Finally,acommunitycanexperienceanemploymentshockthatmightaffectboththe demographicmixofworkersanddemandforthiscompany's products. Inoneset of specifications, we compare the effects of changing demographics on sales over time within store, holding constant regional shocks to sales or work forced emographics that might also affect a near by store.

## Summary

Westudytwodistincteffectsofemploymentdiversityonsales,thefir streflecting customerpreferences,thesecondadirectoutputeffectirrespectiveofcustomerdemographic preferences. The results can be briefly summarized as follows:

- Evidencesuggeststhatsalesarehigherifemployeesspeakthelanguageofcustomers whodonotspeakEnglish.
- Withthatexception,ourresultsdonotsupporttheoriesthatemployee -customermatch increasessales. The effects of employee -community matchare usually small and statistically insignificant.
- Previoustheoriessuggestthatdi versityofgenderorracemightreducesalesduetoworse communicationandcooperationamongworkers,orraisesalesduetopooling information,sparkingcreativity,andunderstandingdiversecustomers.Ourresults supportneithersetofhypotheses.Rac ialandgenderdiversityaregenerallynot correlatedwithsales.
- Diversityofageconsistentlypredictslowersales. Wemustkeepinmindhowyoungand narrowlyclusteredthisworkforceiswhendeterminingthecostsofagediversityinthis sector: A28 yearoldisanunusuallyoldemployeeinthisfirm.

#### Limitations

Our results may be subject to several upward or downward biases. Moreover, even if they are accurate at this employer, they may not generalize to other sectors.

There are several sources of misme a surement of the employee -customer match. For example, we are unable to measure how far customers travel to purchase goods and services from this work place, and this distance varies by store. Moreover, in our interviews, several managers report that they often find employees by approaching customers and encouraging them to apply for a job. If this pattern is common, the actual match will usually be better than our

measuresindicate.Mismeasurementalsoarisesbecausewemerelytabulatethedemo graphicsof thoselivingnearaworkplace;ideallywewouldweighteachdemographicgroupbyits expendituresinthisemployer's sector. In addition, the relatively rapid turnover of employees implies that stores may not form strong reputations for their demographic mix. Moreover, the within-store estimates systematically remove the persistent portion of a store's demographic mix; thus, these estimates ignore effects that operate through the store's reputation for having a particular mix of employees. Ea choft hese forms of mismeasurement is likely to bias down the coefficient on store -community match.

Offsettingthesepotentialdownwardbiases, it is likely that unmeasured neighborhood advantages are more common instores with close customer - employeem at ches. Such advantages will bias the coefficients on customer - employeem at chupward, particularly in the pooled and between - store estimates. To see this effect, note that ethnic mismatch is typically smallest incommunities with a very high proportion white in a community is highly correlated with many other advantages such as higheducation and income (Currie and Duncan, 2000). Thus, unmeasured advantages may predict both low mismatch and high sales.

Atthesam etime, this potential upward bias may be offset be cause the company knows something about the advantages and disadvantages of each community, and may avoid placing work places in disadvantaged communities. Low stored ensity in disadvantaged communities implies relatively high sales per store.

Even if the estimates are unbiased at this employer, they may still not generalize to other employers or too ther sectors of the economy. At the same time, the retail and restaurant sectors employroughly one sixth of the U.S. work force, so results that apply only in these sectors are still important.

Ontheonehand, diversity may matter less in this sector than elsewhere. These work places demandre latively little employee - customer interaction. Thus, there is below-average incentive for customers to see kaclose match. The low status of these jobs implies that customers may care less about the race of those that serve them; for example, many customers may prefer a nolder white male to be their lawyer, but be happy to have a young Hispanic woman be their wait ressorre tail clerk.

Thisemployerhasastrongnationalbrand. It is plausible that potential customers react more to the brand than to the demographics of current employees. Sales might be more responsive to employee - customers imilarity at smaller employers without astrong branding.

Diversity will also matter less in this sector than else where because front line workers have so little discretion. In work places with more decision making power, diversity may be helpful in spurring creativity and costly in terms of raising communication costs. All of these forces are muted here.

Moreover, employees who work in demographically dissimilar communities may be more familiar with the local customers' group that not not expect the interverse and only the interverse of the in

Ontheotherhand, the effects of diversity on sales may be greater in this sector than in others. It is easy for customers in mall sand down townshopping districts to look in the store window, see the demographic match, and choose a store based on similarities. In such a setting, customers may be particularly sensitive to demographic differences with potential sales people.

Inareaswithhighpopulationdensity,thisemployeroftenhasmultipleworkplacesin nearbyshoppingdistricts,andlikemanyemployers,mayfaceincentivestosegregateits workforcesothateachworkplacespecializesinasingledemographicgroup(Becker,1957).In somecases,achainofworkplacescanmaximizeperformanceindiversecommunitiesby operatingmultiplestores,eachofwhichhasahomogeneousworkforceandappea lstoadistinct segmentofcustomers.Forexample, Garson(2002)describesseveralethnicallydistinct shoppingmallsinthediversecity -stateofSingapore.Eachmallservesspeakersofaspecific language.Theemployerinthisstudy,unlikemost,can haveseveralworkplacesinacommunity, eachofwhichhasadistinctworkforceandservesadistinctcustomerbase.Ourmeasure,by poolingthecommunity,woulderroneouslyreportpooremployee -customermatchinallofthe stores.

Someresultswiththis dataset,unlikethetestreportedhere,dosupporttheimportanceof similarityattraction(LeonardandLevine2002).Forexample,m en,olderworkers,whites,and blacks(butnottheothergroups)havelowerturnoverwhentheyworkaroundmanysimilarco workers.Similarly, blacksandAsians(butnotwhitesorHispanics)turnoverlesswhen customersaremorelikelytosharetheirrace.

#### Conclusion

AsianimmigrantswhodonotspeakEnglishapparentlybuymorefromthoseofsimilar background. Beyondthat result, wefind no consistent evidence that most customers care whether the sale speople whose rve the mare of the same race or gender. Additionally, we have aimed to test whether employment diversity might still affect performance through a direct effect onteamwork among employees. We find no consistent evidence that the work group's performance depends on its racial or gender diversity, identified as a nonlinear effect. Age diversity, in contrast, does predict lowers ales. While the effects of diversity yvary, these results do not support the claim that employeed iversity is important because customers desire to be served by those who physically resemble them (e.g., Cox, 1993; Jackson and Alvarez, 1992).

Itispossiblethatcustomersdiscriminateinot hersectors. Moreover, workgroup diversity's effects for both good and illarelikely strongerins ettings where employees have more discretion and autonomy, where work groups are more stable, and where relations with customers are more complex.

Tothose concerned with the long and troubled history of discrimination, and with its continuing specter in this country, these results should be heartening. After all, one of the painful paradoxes of customer discrimination is that it could lead employers to discriminate in pursuit of greater profits even if they are in different torace and gender issues. The paradoxis he ightened by diversity proponents who argue that customers discriminate and should be pandered to. At least at this work place, race and gender diversity do not appear costly. Moreover, managers in mostly white communities will not suffer lowers ale sift hey hire black, Hispanic, or Asian employees. Neither the potential customers nor the employees 'performance as measured by sales is much affected by the race or gender diversity of the work place. This is goodnews.

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Table1:SummaryStatistics

Pooleddata		One-yearchanges	
Mean	Std.Dev.	Mean	Std.Dev.
(omitted)	0.658	(omitted)	0.180
(omitted)	0.505	0.127	0.237
24.3	2.28	-0.213	1.727
0.750	0.137	-0.004	0.089
0.119	0.134	0.013	0.071
0.100	0.131	0.007	0.060
0.070	0.089	0.006	0.054
595.1	115.4	-10.4	87.9
0.582	0.204	-0.006	0.129
0.032	0.070	0.006	0.038
0.027	0.074	0.002	0.032
0.013	0.037	0.002	0.021
0.270	0.062	0.004	0.047
0.337	0.140	0.005	0.088
0.392	0.207	0.018	0.112
0.512	0.017		
0.075	0.094		
0.051	0.069		
0.051	0.078		
0.005	0.011		
0.005	0.015		
0.262	0.017		
0.014	0.047		
0.007	0.030		
0.009	0.047		
0.499	0.002		
0.318	0.184		
		communityva	ariableand
0.238	0.138	-	0.046
			0.014
			0.009
			0.003
			0.013
0.001	0.004	0.0001	0.0014
	Mean (omitted) (omitted) (omitted)  24.3 0.750 0.119 0.100 0.070 595.1 0.582 0.032 0.027 0.013 0.270 0.337 0.392  0.512 0.075 0.051 0.005 0.005 0.005 0.005 0.262 0.014 0.007 0.009 0.499 0.318  0.238 0.015 0.008 0.001	Mean         Std.Dev.           (omitted)         0.658           (omitted)         0.505           24.3         2.28           0.750         0.137           0.119         0.134           0.100         0.131           0.070         0.089           595.1         115.4           0.582         0.204           0.032         0.070           0.027         0.074           0.013         0.037           0.270         0.062           0.337         0.140           0.392         0.207           0.512         0.017           0.075         0.094           0.051         0.069           0.051         0.078           0.005         0.011           0.005         0.011           0.005         0.011           0.007         0.030           0.009         0.047           0.499         0.002           0.318         0.184           0.238         0.138           0.019         0.061           0.008         0.036           0.001         0.006	Mean         Std.Dev.         Mean           (omitted)         0.658         (omitted)           (omitted)         0.505         0.127           24.3         2.28         -0.213           0.750         0.137         -0.004           0.119         0.134         0.013           0.100         0.131         0.007           0.070         0.089         0.006           595.1         115.4         -10.4           0.582         0.204         -0.006           0.032         0.070         0.006           0.027         0.074         0.002           0.013         0.037         0.002           0.270         0.062         0.004           0.337         0.140         0.005           0.392         0.207         0.018           0.512         0.017         0.018           0.051         0.069         0.051           0.052         0.017         0.015           0.262         0.017         0.014           0.005         0.015         0.020           0.318         0.184         Changesuse communityva changein%of           0.238         0.138 <t< td=""></t<>

 $The sample contains over 20,000 store \quad -months at over 800 stores. Between \quad -stores ummary statistics resemble pooled.$ 

Table2:PooledTimeSeriesCrossSe ction&BetweenStores

	(1)Baseline Pooled	(2)Interactions Pooled	(3)Diversity Pooled	(4)Interactions Between	(5)Diversity Between
DependentVariable	LogReal MonthlySales	LogReal MonthlySales	LogReal MonthlySales	Log(Average realsales)	Log (Average realsales)
StoreEmployeesAvg.Age	0.004**	0.023**	0.007**	0.020	0.020**
Store%Female	(0.001) -0.024	(0.009) 0.006	(0.001) -0.002	(0.042) -0.390**	(0.005) -0.348*
Store%Black	(0.016) -0.078** (0.020)	(0.023) -0.003 (0.035)	(0.033) -0.118** (0.027)	(0.141) -0.064 (0.164)	(0.156) -0.408** (0.098)
Store%Hispanic	0.020) 0.030 (0.024)	0.047 (0.038)	-0.011 (0.030)	0.661** (0.194)	-0.050 (0.120)
Store%Asian	0.058* (0.026)	0.015 (0.041)	0.010 (0.035)	-0.132 (0.247)	-0.456** (0.160)
Community%Female	1.123** (0.434)	1.138* (0.449)	1.117* (0.457)	-0.852 (0.552)	-0.798 (0.547)
Community%Black	-0.455** (0.076)	-0.526** (0.144)	-0.475** (0.116)	-0.329 (0.192)	0.063 (0.154)
Community%whiteHispanics	0.578** (0.124)	0.756* <sup>′</sup> (0.321)	0.586** (0.142)	0.001 (0.450)	0.448* <sup>´</sup> (0.199)
Community%Asian	0.133 (0.084)	0.443* (0.220)	0.121 ´ (0.101)	0.061 (0.317)	0.421** (0.161)
(StoreAvg.Age) <sup>2</sup>	,	-0.000* (0.000)	, ,	-0.000 (0.001)	, ,
(Store%Black) <sup>2</sup>		-0.176* (0.069)		-0.374 (0.332)	
(Store %Hispanic) <sup>2</sup>		-0.141 (0.108)		-1.398** (0.521)	
(Store%Asian) <sup>2</sup>		0.133 (0.146)		-0.361 (0.905)	
(Community%Black) <sup>2</sup>		0.178 (0.307)		0.233 (0.474)	
(Community%Hispanic) <sup>2</sup>		-0.475 (0.639)		0.200 (1.044)	
(Community%Asian) <sup>2</sup>		-0.503 (0.357)		0.054 (0.807)	
Topquartile (Store%Female –Community %Female)		0.003 (0.005)		0.009 (0.027)	
Bottomquartile		0.012**		-0.028	
(Store%Female –Comm.%Female)		(0.004)		(0.025)	
(Store%black)*(Community%black)		0.012 (0.156)		0.448 (0.551)	
(Store%Hispanic)*		0.230		0.881	
(Community%Hispanic) (Store%Asian)*(Community%Asian)		(0.215) -0.038 (0.269)		(0.720) 0.617 (1.488)	
StoreAgeDiversity =S.D.(log(age))		(0.203)	-0.157** (0.039)	(1.400)	-0.821** (0.195)
StoreGenderDiversity			0.022		-0.110
=1 -[(%female) <sup>2</sup> +(%male) <sup>2</sup> ]			(0.034)		(0.163)
StoreRacialDiversity =1 -[(%W) <sup>2</sup> +(%B) <sup>2</sup> +(%H) <sup>2</sup> +(%A) <sup>2</sup> ] $\mathbb{R}^2$	0.78	0.78	0.046* (0.022)		0.278** (0.094)

Table3: Year -on-YearChanges

## DependentVariable=1year%changeinsales

	Entiresample		Samplecontainsstoresthathaveat leasttwostoresinthesameZIP	
	(4)	(0)Diit	code	(4) Discouring
A	(1)Interactions	(2)Diversity	(3)Interactions	(4)Diversity
ΔAvg.AgeintheStore	0.006	0.004**	-0.004	0.005**
0. 40/5	(0.007)	(0.001)	(0.008)	(0.001)
Store Δ%Female	-0.394	-0.014	-0.169	-0.005
	(0.379)	(0.030)	(0.410)	(0.034)
Store Δ%Black	-0.078**	-0.044*	-0.037	-0.041
	(0.029)	(0.022)	(0.034)	(0.027)
Store Δ%Hispanic	-0.041	0.023	-0.047	0.022
	(0.032)	(0.025)	(0.035)	(0.028)
Store Δ%Asian	-0.010	0.084**	0.064	0.089**
	(0.032)	(0.027)	(0.036)	(0.031)
$\Delta$ (Avg.AgeintheStore $^2$ )	-0.000		0.000	
	(0.000)		(0.000)	
Store Δ(%Black <sup>2</sup> )	-0.014		0.044	
,	(0.061)		(0.073)	
Store Δ(%Hispanic <sup>2</sup> )	0.143 <sup>′</sup>		Ò.134 <sup>′</sup>	
( )	(0.093)		(0.099)	
Store Δ(%Asian <sup>2</sup> )	0.373**		0.095	
(	(0.128)		(0.154)	
(Store Δ%Female)*(Community%Female)	0.804		0.344	
(0.0.0 = 70. 0) (00	(0.742)		(0.804)	
(Store Δ%Black)*(Community%Black)	0.072		-0.447*	
(Otoro 1270 Black) (Community 70 Black)	(0.152)		(0.184)	
(Store Δ%Hispanic*(Comm.%Hispanic -allraces)	-0.183		-0.129	
(Otore 1270) hoparile (Oorinn. 70) hoparile ainaces)	(0.204)		(0.238)	
(Store Δ%Asian)*(Community%Asian)	-0.671**		-0.477	
(Store A70Asian) (Community 70Asian)	(0.225)		(0.269)	
Store Δst.dev.ln(age)	(0.223)	-0.071*	(0.209)	-0.112**
Store Ast.dev.in(age)				(0.034)
Store ACandar Divargity		(0.031)		(0.034) -0.012
Store ΔGenderDiversity =1 -[(%female)²+(%male) ²]		-0.031 (0.030)		
		(0.029)		(0.032)
Store $\triangle$ RacialDiversity		-0.040*		-0.042*
=1 -[(%white)²+(%black)²+(%Hispanic)²+(%Asian)²]		(0.016)		(0.019)
Observations:stores	over800	over800	over600	over600
store -months	over20,000	over20,000	over10,000	over10,0 00
Numberof5 -digitZIPcodedummies	0	0	over300	over300
R-squared	.239	.240	.338	.338

Within-StoreEstimates

AddingZIPCodeFixedEffects

Notes:Standarderrorsinparentheses.\*significantat5%;\*\*significantat1%.Additionalcontrolsincluded%changein employment,storeageanditssquare,t imesincelastremodelanditssquare,storesizeinsquarefeetanditssquare, store division,storelocationtype(mall,street,etc.;col.1only), \( \Delta \text{NativeAmericans}, \( \Delta \text{% otherraces}, and month dummies. \)
Standarderrorsareadjustedforfirst -orderautocorrelationwithinstoresandforheteroskedasticityacrossstores.

Table4: ResultsConcerningtheLinguisticallyIsolated

Specification	PooledTime SeriesCross Section	Between stores	Year-on-Year Changes	Year-on-Year ChangeswithZIP codefixedeffects
Dependentvariable	LogRealMonthly Sales	Log(Average realsales)	Oneyear %changeinsales	Oneyear%changein sales
Controlsandsampleasin:	Table2,col.2	Table2,col.4	Table3,col.1	Table3,col.3
(Store%Hispanic)*	0.199	1.001	-0.112	-0.342
(Comm.%Hispanic -allraces)	(0.265)	(0.789)	(0.277)	(0.326)
(Store%Asian)*	-0.574*	-0.586	-1.238**	-1.007**
(Community%Asian)	(0.285)	(1.517)	(0.246)	(0.313)
(Store%Hispanic)*	0.898	-0.805	-0.955	2.335
(Community%speakingonly Spanish)	(1.831)	(4.157)	(1.769)	(2.503)
(Store%Asian)*	7.058**	15.414**	8.654**	5.709**
(Community%speakingonly anAsian -Pacificlanguage)	(1.264)	(5.155)	(1.701)	(1.885)

Notes: Each column represents a subset of the coefficients from a separate regression specification. Other controls include the percent speaking only an Asian - Pacific language, the percent speaking only Spanish, and the additional variables as indicated at the topo feach column. The proportions speaking only Spanish or an Asian language measure people who do not speak English; they may speak other non - English languages. The first - differences specifications (col. 3 and 4) include first differences of store variables, but not community ones.

(11/18/02)