Workforce Diversity and Productivity: An Analysis of Employer-Employee Matched Data

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Abstract

Calls for workforce diversity abound; arguments in support of diversity at the workplace suggest that we are a better society when we work together. In a recent opinion poll, 81% of respondents said that it is somewhat or very important “to have employees of different races, cultures and backgrounds in the workplace or businesses.” However, the actual economic costs and benefits to workforce diversity are unclear. The goal of this paper is to empirically assess the relationship between workforce diversity and the economic performance of an establishment. We use the New Worker-Establishment Characteristics Database (NWECD), a nationwide employer-employee matched data set, to estimate the association between productivity and workforce diversity. These data allow us to overcome many of the limitations of past studies because the NWECD is an establishment-level data set. Our main finding is that diversity is either positively associated with productivity or there is no significant relationship between diversity and productivity. We never find a significant negative relationship between establishment-level diversity and productivity. This leads us to conclude that establishments that employ a more diverse workforce are no less productive than establishments that employ a more homogeneous workforce.

I. Introduction

Calls for workforce diversity abound; arguments in support of diversity at the workplace suggest that we are a better society when we work together. In a recent opinion poll, 81% of respondents said that it is somewhat or very important "to have employees of different races, cultures and backgrounds in the workplace or businesses."[1] Diversity appears to be a social goal for the workplace, as well as schools and neighborhoods. Businesses are under pressure to achieve diversity because it is the "right" thing to do and because a homogeneous workforce may be evidence of discrimination.

While there is pressure on businesses to achieve a diverse workforce, there is very little existing evidence on the effects of diversity on firm performance. One obvious question is whether we should expect any relationship between diversity and firm performance. If firms were being forced to hire diverse workers through governmental affirmative action policies, and firms were currently discriminating against either female or minority workers, then diversity could have a positive impact on firm performance because firms would be forced to hire workers whose wages were less than the value of their marginal product. Alternatively, if there were no discrimination in the labor market, if it were more costly to recruit and hire qualified minority and female workers, or if firms must spend resources on programs, such as diversity training, to overcome the discriminatory preferences of existing workers, then diversity may have a negative impact on firm performance.

In a non-discriminatory market, there could also be a positive relationship between diversity and firm performance, prompting profit-maximizing businesses to voluntarily seek diverse workers. To the extent that the general public views a diverse workforce as a desirable attribute for a firm, firms that have this attribute may acquire goodwill capital or brand loyalty.[2] This could be viewed as a way for firms to decrease the elasticity of demand for their product,

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[1] American Council on Education, "New National Poll on Diversity" Press Release, August 13, 2000 (Washington, DC). See http://www.acenet.edu/news/press_release/2000/08august/diversity_poll.html.

[2] Certainly negative public-opinion campaigns directed at businesses viewed as anti-women or anti-minority can inflict high costs. A recent example is the Fall 2000 case of the regional company, Maurice's Gourmet Barbecue Sauce. Within weeks of the first public criticism of founder and chief Maurice Bessinger's "racist" actions (including selling propaganda advocating slavery on biblical grounds at the company's headquarters), Maurice's lost the majority of its largest vendors who had been providing up to half its sales revenues (DiversityInc.Com, Sept. and Oct. 2000, Allegiant Media Inc.).

thereby allowing them to charge a higher price and increase profits (Navarro, 1988). In addition, profit maximization may require workforce diversity if a firm sells its product in many markets and diversity helps to understand different market preferences (Osborne, 2000). In the end, whether the net economic benefits of workforce diversity are positive or negative is an empirical question.

The goal of this paper then is to examine the empirical evidence on the relationship between workforce diversity and the economic performance of an establishment. In this study we narrow the definition of economic performance to establishment-level labor productivity and empirically assess the association between workforce diversity and labor productivity. Data constraints have limited most previous research in this area to cross-industry comparisons using aggregated statistics, or to case studies, making the results vulnerable to criticism. Cross-industry analyses do not detect production-related intra-industry variation, which can be substantial (Haltiwanger, Lane, and Spletzer, 2000). Furthermore, it is not uncommon for such studies to omit average operational scale or other explanatory factors of production. Case studies, on the other hand, may benefit from richer production-related data, but the degree to which the results of such studies are applicable beyond the business or industry being studied is limited.

We use the New Worker-Establishment Characteristics Database (NWECD), a nationwide employer-employee matched data set, to estimate the association between productivity and workforce diversity. These data allow us to overcome many of the limitations of past studies because the NWECD is an establishment-level data set. The NWECD matches workers who responded to the long form of the 1990 Decennial Census to the establishments where they work, using the U.S. Census Bureau's Standard Statistical Establishment List (SSEL). The NWECD includes workers and establishments from all sectors of the economy. Thus, we provide new estimates of the relationship between diversity and productivity using a large data set containing establishments operating in nearly all regions and industries. Consequently, we can examine the relationship between diversity and productivity separately for workers in different industries. We focus here on the three largest industries in our data: manufacturing, retail trade, and services. Our primary measure of productivity is labor productivity or log value added per worker (measured as total sales minus total payroll divided by the number of workers in the plant). We also construct an alternative labor productivity measure as log total sales per worker (total sales divided by the number of workers in the plant). One shortcoming of these data is that they do not contain measures of capital stock or material inputs for establishments in sectors other than manufacturing, limiting us to using labor productivity measures. To the extent that the characteristics of workers in an establishment are correlated with these other inputs, this may bias our results. Using the data on manufacturing plants, we also examine the relationship between multi-factor productivity and workforce diversity.

The richness of the NWECD allows us to construct multiple measures of workforce diversity. We introduce a unique measure of workforce diversity and compare the results found using this new measure with results found using more traditional measures of workforce composition, namely, "percent white men," "percent minority men," etc. The unique diversity measure we introduce has two components. The first component captures the combined race and gender diversity of the establishment's workforce; the second captures how that establishment's diversity is spread across occupations. The use of more than one measure of workforce diversity provides an important sensitivity test and reveals that how one defines diversity is important.

Our main finding is that diversity is either positively associated with productivity or there is no significant relationship between diversity and productivity. We never find a significant negative relationship between establishment-level diversity and productivity. This result holds for establishments in all three industries and is robust across our alternative measures of productivity and diversity. This leads us to conclude that establishments that employ a more diverse workforce are no less productive than establishments that employ a more homogeneous workforce.

The rest of the paper is organized as follows. In the next section we discuss related studies. Section III contains a discussion of our data and measurement issues. Our results are presented in Section IV. Section V concludes and presents some caveats.

II. Related Literature

In considering the relationship between workforce diversity and economic performance, the question that first arises is "Why *should* there be a relationship between diversity and economic performance?" The answer to this question depends in part on whether or not discrimination is present in hiring practices. Discrimination—hiring workers based on race or gender instead of ability—results in a firm's hiring workers who are paid higher wages than alternative workers, but are no more productive (Becker, 1971). Forcing firms to become more diverse through governmental affirmative action policies could then increase economic performance because businesses would be forced to hire workers whose wage is less than or equal to the value of their marginal product. [3] If discrimination were not present in hiring decisions however, forcing businesses to hire women and minorities could result in the hiring of less productive workers, leading to lower productivity for the firm.

However, even if forcing firms to hire diverse workers did result in increased productivity, there could be costs associated with increasing workforce diversity that could offset any gain. Such potential costs include increased costs associated with recruiting and hiring women and minorities (Holzer and Neumark, 2000b), and costs associated with getting a heterogeneous workforce to work together (Osborne, 2000). If workers self-select into employment based on the race, gender, or religion of co-workers, a firm attempting to create a diverse workforce may lower the utility of existing workers who may in turn shirk or take other actions costly to the firm. The firm may therefore have to incur other costs, such as providing diversity-training courses, in an effort to change the preferences of current workers. A diverse workforce could also negatively impact productivity if diversity introduces communication and cooperation challenges not present among homogeneous workers (Lang, 1986).

Holzer and Neumark (2000a) and Altonji and Blank (1999) provide recent and extensive reviews of the evidence on discrimination in the labor market. Holzer and Neumark conclude, "that the overall evidence points to some continuing discrimination against women and blacks" (p 493), although the evidence is by no means conclusive. Continuing discrimination against women and blacks would suggest performance gains could follow from increased workforce diversity.

[3] Firms with more than 50 employees who do business with the federal government, and all firms with more than 100 employees, are required to file yearly reports with the Equal Employment Opportunity Commission (EEOC) on the percent of women and minority workers in the firm. These reports can then be used by the EEOC to file discrimination lawsuits (Bloch, 1994). In the opinion of Bloch (1994, p. 105), "noncontractors required to file EEO-1 reports that are monitored by the EEOC … would not be acting rationally if they were to avoid hiring minorities and women."

The most significant difference between affirmative action, which is the focus of Holzer and Neumark's (2000a) review, and our focus on workplace diversity is that affirmative action is designed to produce social gains, whereas from the firm's perspective, only private gains are relevant. To the degree that the performance gains from increased diversity in a discriminatory environment can be internalized by the employer, and not off-set by accompanying higher costs, a positive relationship should be found between workforce diversity and economic performance.

However, there may be other private gains from increasing workforce diversity. Navarro (1988) presents a theory in which firms use corporate charitable giving as a way to promote the firm's image. This in turn provides goodwill capital to the firm that acts to either shift out or to decrease the elasticity of the firm's demand curve. In either case, charitable giving is a profit maximizing act on the part of the firm. To the degree that workforce diversity is seen as a desirable social goal, the firm could view having a diverse workforce as another way to invest in goodwill capital.

Alternatively, workforce diversity may actually contribute to the *production* of a higher-quality or unique product.[4] Osborne (2000) argues that profit maximization may lead to workforce diversity if a firm sells its product in many markets, and that product has multiple characteristics that are valued differently in the different markets.[5] The firm will optimize its workforce diversity with respect to "the product's characteristics, the extent to which different markets value them, and the extent to which [demographically diverse] groups inherently differ in their capacity to provide" these characteristics (p 473).

Data constraints have limited most research attempting to empirically examine the relationship between diversity and productivity to cross-industry comparisons using aggregated statistics or to case studies. For example, Heckman and Payner (1995) study the textile industry

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[4] A diverse workforce producing a better product than that produced by a homogeneous workforce is analogous to the argument that diverse student bodies in colleges and universities produce better educational experiences. Students, being an input into the educational end product, as well as consumers thereof, the argument goes, will create a richer (better) educational product if they are more diverse (see Holzer and Neumark, 2000a, p 528). In the case of busing-style integration, however, it is also argued that positive peer effects from privileged students will benefit the less privileged, without net harm to the education of the more privileged. This education-focused argument does not have a clear business analogy.

[5] One example of this may be General Motors' recently announced initiative to increase the number of women in charge of car dealers so that the characteristics of their dealers better matches the characteristics of their customers, 50 percent of whom are women (St. Louis Post-Dispatch, March 21, 2001, p. C8.).

in South Carolina and show that affirmative action programs increased black employment during a period of increasing productivity in textiles. In a 1986 study of medical school graduates, Penn, et al. (1996) find that minority-recruitment graduates saw more patients per day and were more likely to serve rural and inner city communities and low-income patients, both possible measures of productivity. And, in a 1987 study of police departments, Steel and Lovrich (1987) find that departments with active affirmative programs showed no statistical difference in crime rate, clearance rate (crimes solved), and operation costs. However, in a study of the effect of affirmative action policies on police departments, Lott (2000) finds that increasing police force diversity negatively affects productivity.

Studies using aggregate data, such as state level manufacturing data or inter-industry data, have generally found no negative repercussions from increased workforce diversity. In analysis of state level manufacturing data over the period 1966 to 1977, Leonard (1984) finds that changes in the female or minority employment percentages had no significant impact on industry productivity after controlling for region, industry, capital stock, and the percentage of the industry employment that was blue collar. A study of 57 industries revealed changes in the female or black employment percentages between 1984 and 1988 had no significant impact on industry productivity (Conrad, 1995).

Research using employer-employee matched data to study the relationship between diversity and productivity, however, is almost non-existent. One exception is the Holzer and Neumark (2000b) study which examines data from a 1992-1994 survey of 3200 employers in Atlanta, Boston, Detroit, and Los Angeles on the establishments' affirmative action policies and the last employee hired. These data revealed that employers who have active affirmative action policies in *recruitment* seem to locate more-qualified candidates who are women and minorities. Employers that have active affirmative action policies in *hiring* do hire women and minorities with somewhat weaker credentials, but the performance of these employees is not weaker than that of their peers. Performance is measured by the supervisor's rating of the employee, not by any measure of total establishment output. Additional training and evaluation programs for affirmative action hires may have been responsible for the satisfactory productivity of those hired with weaker credentials (Holzer and Neumark, 2000b).

The New Worker-Establishment Characteristics Database (NWECD) that we use for this study can greatly improve upon past analysis of the relationship between workforce diversity and productivity by allowing us to simultaneously control for establishment and worker characteristics and eliminating problems introduced by using aggregated data. Work using employer-employee matched data have already proven a rich source for studies related to worker characteristics. Hellerstein, Neumark and Troske (1999) investigate the role that age, race, and gender play in accounting for wage and productivity differences across plants. Among other results, they find that "women's wages fall short of men's by considerably more than can be explained by their lower marginal productivity. This is consistent with the standard wage discrimination hypothesis." (p 433). With regard to African American manufacturing workers, however, they find no evidence of wage discrimination.

A different empirical test of the relationship between economic performance and workforce diversity is to let the market "speak for itself." If a company's stock price signals economic performance—present or future—then the movement of a company's stock price vis-à-vis its workforce diversity should reveal if a relationship exists between workforce diversity and economic performance. Wright, et al. (1995) and Welbourne (2000) both find that the stock market rewards owners of firms for increased diversity. Wright, et al. report that companies recognized by the U.S. Department of Labor for having an exemplary affirmative action program experience an increase in stock price immediately after the announcement. Welbourne reports that having a diverse management team at the time of the initial public offering of a company's stock results in a higher stock price than that received by similar companies with more homogeneous management teams. The results from both of these studies suggest that the stock market does see net financial benefits accruing to companies with greater diversity.

It is worth noting that the positive relationship between workforce diversity and stock price does not show exactly what the market is rewarding. It may be that the market interprets diversity as providing a revenue edge through increased goodwill capital. Alternatively, it may be that diversity is viewed simply as a proxy for good management—a signal that this must be a well-managed company because well-managed companies are more diverse, not that diversity will make the company more profitable.[6] The lack of *causal* evidence on the relationship between diversity and economic performance is a point we pick up later when discussing our own results.

III. The Data and the Measurement of Variables

The New Worker Establishment Characteristic Database

The NWECD is a cross-sectional data set linking workers' responses to the 1990 Decennial Census long form to establishment data drawn from various economic censuses. Since these data are constructed in the same way as the original Worker Establishment Characteristics Database (Troske, 1998), and are documented extensively elsewhere (Bayard, Hellerstein, Neumark, and Troske, 1998), we only briefly describe these data. The NWECD was constructed by matching worker records from the 1990 Sample Edited Detail File (SEDF) to establishment records from the 1990 Standard Statistical Establishment List (SSEL). The 1990 SEDF consists of all household responses to the 1990 Decennial Census long form. Individuals receiving the long form were asked to identify each employed household member's occupation, employer location, and employer's industry. The Census Bureau then assigned occupational, industrial, and geographic codes to these long-form responses. Thus, the SEDF contains standard demographic information for all respondents as well as detailed location and industry information for each respondent's place of work.

The SSEL is a complete list of all establishments in the U.S. in a given year and is used by the Census Bureau to administer various economic censuses and surveys. The SSEL contains detailed location information for all establishments along with a four-digit SIC code and a unique establishment identifier that is common to other Census Bureau economic data.

Worker records from the SEDF are matched to employer records in the SSEL using the common industry and location information for employers available in both data sets. Briefly, the matching process proceeds as follows. First, only establishments that are unique to an industry-location cell are kept. Then all workers who indicate they work in the same location-industry

[6] See Cappelli and Neumark (1999), and Black and Lynch (forthcoming, 2001) for studies that try to isolate managerial practices from other causes of better economic performance.

cell as a retained establishment are linked to that establishment. These matched data are what are contained in the NWECD. Because the SEDF contains only a sample of workers, and because not all workers were matched, the NWECD contains a sample of workers in any given establishment.

To obtain the data used for this project we impose several restrictions on the NWECD data. First, we only keep establishments with more than 25 employees. Measures of per worker earnings taken from the SSEL and SEDF are closer for larger than smaller establishments; thus we believe the data are of higher quality for larger establishments. In addition, again because of concerns about data quality, we eliminate workers in establishments where the average salary is greater than \$600,000. To obtain additional information about a worker's employer, we match the NWECD to establishment-level data from the 1987 Censuses of Manufacturing, Retail Trade, and Services. We choose to focus on workers in these industries since they are the industries containing the largest number of workers in our data.

Evidence presented in Bayard, Hellerstein, Neumark and Troske (1998) suggests that workers are correctly matched to establishments, and that wage regressions using these matched data are unlikely to be biased from sample selection associated with the matching process, even though the data set is non-representative. One of the main sources of this non-representativeness is that the NWECD over-samples workers in manufacturing and under-samples workers in retail trade. This fact provides additional justification for why we choose to analyze workers separately by industry.

Workforce Demographics

From the NWECD we construct various establishment-level measures of workforce characteristics relevant to our analysis. Using the data on matched workers we construct measures of the workforce demographics of the establishments. These include percent white male workers, percent minority male workers, percent white female workers, percent minority female workers, percent older workers, and percent college graduates. Each of these is measured as the number of workers matched to the establishment in a given group divided by the total number of workers matched to the establishment. We classify workers of all races other than white, along with all Hispanic workers, as minority workers. In this paper, white workers means non-Hispanic white workers. Older workers are defined as those over 50 years old.

Payroll and Occupational Diversity Measures

Previous studies of the effect of diversity have used measures of workforce characteristics such as percent white male, percent minority male, percent white female and percent minority female to capture diversity.[7] However a limitation of these measures when applied to establishment-level data is that they do not scale the characteristics of the establishment workforce against a relevant comparison group such as all workers in the industry. Neither do they consider how the establishment's diversity is spread across occupations. We therefore construct an additional and novel measure of workforce diversity. This measure gauges the establishment's workforce diversity through two distinct comparisons. The first comparison answers the question "How diverse is the establishment's workforce, or payroll, relative to the workforce in the establishment's industry?" We refer to this as the payroll diversity term. The payroll diversity term gauges the overall workforce diversity of the establishment relative to that in its industry using a ratio of the distributions to capture the scale of the deviation between the establishment and its baseline.[8] When constructing this measure we used as our measure of the industry workforce the percent of white males, nonwhite males, white females, and nonwhite females that appear in our NWECD data at the one-digit SIC industry level.

The second comparison, composing our occupational diversity term, answers the question "How evenly is the diversity present in the establishment spread across occupations?" The occupational diversity term captures the occupational distribution of the establishment's workforce diversity by measuring the difference between the establishment's actual occupational

[7] The advantage of these measures is that they are both easy to compute and easy to interpret.

[8] See MacKenzie (1999) for a measure of diversity built on the difference of distributions. We have also constructed diversity measures that compute the overall workforce diversity of an establishment relative to that in the establishment's region, and to that present in the NWECD (nationwide) sample. We also used as the baseline the characteristics of workers in the entire SEDF data (which are a true random sample of the population). The estimated relationship between these additional diversity measures and productivity are qualitatively similar to the relationship between our primary diversity measures and productivity. We report the results using the diversity measure that compares establishment-level diversity relative to that of its industry because the industry workforce is a reasonable proxy for the establishment's relevant labor pool, and because of the similarity of results using regional and national baselines.

distribution of workers for each race-gender category and a hypothetical distribution where the establishment's workforce is spread across occupations independent of race and gender. As in the payroll diversity term, the scale of the deviation between the establishment's observed distribution and baseline distribution is captured by the ratio of the observed to the baseline distribution. This measure allows us to distinguish between employers that employ a more diverse workforce but segregate workers by occupation within the establishment and employers that have a diverse workforce within occupations. We use the EEOC's nine occupational categories when defining occupation. To repeat, the first term captures how diverse the workforce is compared to the workforce of the industry (the payroll diversity), and the second term captures how evenly the diversity present in the establishment is spread across occupations (occupational diversity).[9]

The arithmetic formula used to translate the ratios into a single numeral for each term was devised to produce an index that ranged from 0 to1. A value of 1 for the payroll diversity term indicates that the race-gender diversity of the establishment perfectly matches the baseline distribution. A value of 1 for the occupational diversity term indicates that the establishment's employees of each race-gender group appear in each occupation in the same proportions as they appear on the payroll. The exact formulation of this measure appears in the Appendix.

Productivity and Establishment Characteristics

Our two primary measures of labor productivity are constructed using the Economic Census data. They are, 1) the log of value added (measured as total sales minus total payroll) divided by the total number of workers in the establishment, and 2) the log of total sales divided by the total number of workers in the establishment. One problem with these measures is that they do not control for differences in other inputs such as capital stock and materials. Unfortunately, information on capital stock and other materials is only collected for manufacturing establishments. For manufacturing, then, we construct a third measure of

[9] We have also constructed another measure of diversity based on the Chi-Squared test statistic. There are again two terms to this measure, the payroll diversity term and the occupational diversity term. The payroll diversity term is constructed as the test statistic from a test of independence in a contingency table constructed using the distribution of workers in the establishment as the observed values and the distribution of workers in the relevant baseline as the expected values (DeGroot, 1986). The occupational diversity term is constructed in a similar fashion. Both terms are bounded below by zero and have no upper bound. Analysis using this Chi-Squared diversity measure leads to the same conclusions as analysis with our diversity measure (results available upon request).

productivity, multi-factor productivity. This measure should allow us to judge how missing other inputs in the services and retail trade industries affect our results. Multi-factor productivity is measured as:

$$\ln MFP_i = \ln Q_i - \alpha_K \ln K_i - \alpha_L \ln L_i - \alpha_M \ln M_i \tag{1}$$

where Q_i is real output from establishment i, K_i is real capital stock, L_i is total hours worked, and M_i is real value of materials.[10] The α's are the factor elasticities. Factor elasticities are measured as the share of the cost of the input relative to the total cost of all inputs in each four-digit industry. All of the data come from the 1987 Census of Manufacturers.

Finally, we use the establishment data to construct controls for other establishment characteristics that may affect establishment-level productivity such as location in the four Census regions (Northeast, Midwest, South and West), four-digit SIC industry, ownership structure (whether the establishment is part of a single-establishment firm) and size (measured as log total employment).

Table 1 presents summary statistics for the establishments in our data set. One thing to note is that the establishments in our data are fairly large on average. This is due to having eliminated the smaller establishments from the data because of quality concerns, and because larger establishments are more likely to have matched workers and therefore be included in the NWECD (Bayard, Hellerstein, Neumark and Troske, 1998).

IV. Regression Estimates

In the analysis that follows we present results from estimating the following regression equation:

$$\ln Y_i = \beta \mathbf{X_i} + \delta \mathbf{Z_i} + \varepsilon_i \tag{2}$$

[10] This is identical to the measure of multi-factor productivity used in Foster, Haltiwanger, and Krizan (1998). See the discussion there for a more in-depth description of how this measure is constructed. We would like to thank Lucia Foster for providing us with these data.

where Y_i is our establishment-level productivity measure, either log value-added per worker or log sales per worker (and for manufacturing establishments log of multi-factor productivity), $\mathbf{X_i}$ is a matrix containing our establishment-level measures of workforce diversity, $\mathbf{Z_i}$ is a matrix containing other establishment-level controls, and e_i is an establishment-specific error term. Included in $\mathbf{Z_i}$ are, log total employment (Log (TE)), the percent of workers in the plant that are over 50 (Percent Older Workers), the percent of workers in the plant that are college graduates (Percent College Grad.), a dummy variable indicating whether the establishment is part of a firm with no other establishments (Single-Unit), dummy variables indicating which of the four census regions the establishment is located, and a set of dummy variables indicating in which four-digit SIC code the establishment is classified. We estimate equation (2) separately for establishments in manufacturing, services, and retail trade.

Tables 2 through 4 contain our main results. Presented in Table 2 are the regression results using our novel measure of workforce diversity. Focusing first on manufacturing establishments, we see that the coefficient on payroll diversity is positively and significantly related to productivity (at 99%) whether productivity is measured by log(value-added/TE) or log(Sales/TE). However, there is no significant relationship between occupational diversity and productivity in either regression.

Looking at the coefficients on the other variables in columns (1) and (2) we see results that are fairly standard. Larger establishments are more productive than smaller establishments and establishments that are part of single-unit firms are significantly less productive than plants that are part of multi-unit firms. Finally, we see that the percent of older workers is negatively related to productivity while the percent of college graduates is positively related to productivity. The former result is consistent with the results in Hellerstein, Neumark and Troske (1999, 2001) who use the WECD to examine the relationship between worker characteristics and establishment-level productivity and profitability. One concern we have about the estimated relationship between the percent of older workers and productivity is that this negative relationship may be due to the fact that we are not controlling for capital and other materials used in production. It may be that older workers tend to work in establishments with older, less productive capital. As we indicated above, since we do not have any establishment-level measures of capital or materials for establishments in services or retail trade, we are unable to investigate this hypothesis in these industries.[11] However, since we do have this information for manufacturing establishments, we examine this issue below for these establishments.

The results for service establishments mirror the results for manufacturing establishments. Payroll diversity is positively and significantly correlated with both productivity measures while occupational diversity is not significantly related to productivity. The relationship between our other controls and productivity are also quite similar to the relationships estimated using manufacturing establishments.

The estimated relationship between our diversity measures and productivity is notably different for establishments in retail trade. Here neither payroll diversity nor occupational diversity is significantly related to productivity.[12] Our conclusion based on the results in this table is that plants that are more diverse, at least as measured in this fashion, are either slightly more productive, or at least as productive, as less diverse establishments.

One issue about which we are concerned is the role of measurement error in our estimates in Table 2.[13] Since we only have a matched sample of workers in an establishment, our diversity measure for each establishment is only an estimate of the true diversity in the establishment. However, in our regressions we treat these estimates as known variables. In order to try and judge the possible effect of measurement error on our estimates we repeat our previous analysis focusing on establishments with 500 or more employees, what we term large establishments. Given that a larger number and a more representative sample of workers are matched in large establishments (Bayard, Hellerstein, Neumark, and Troske, 1998), the measurement error should be smaller among these establishments. Unfortunately, we have very few establishments in retail trade with more than 500 workers. Therefore, we re-estimate equation (1) focusing only on large establishments in manufacturing and services. The results from these regressions using the payroll and occupational diversity measures are found in Table 3.

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[11] Information about capital stock, capital investment and other materials used in production is only asked of establishments in the Census of Manufacturers.

[12] The association between productivity and both the percent college grad. and the single-unit dummy is also insignificant for retail trade establishments.

[13] See Hellerstein, Neumark and Troske (1999) and the reference therein, for a more complete discussion of the issue of measurement error in this context, and for an assessment of the possible effects of measurement error in a similar setting.

Looking at the results for manufacturing and service establishments we see that among large establishments the payroll diversity measure remain positively and significantly related to both productivity measures. Now however, occupational diversity is also positively and significantly associated with productivity in manufacturing, suggesting that our concerns regarding measurement error were valid. Limiting our sample to establishments with more than 500 workers increased the likelihood of matching more workers in each occupational category. The result is a stronger estimated relationship between productivity and diversity across occupations within manufacturing establishments. These results suggest that, at least for large manufacturing establishments, not only are more diverse establishments more productive but so are establishments that have diverse workforces within occupation.

Among large service establishments, however, the positive relationships between occupational diversity and our measures of productivity do not become significant when the analysis is limited to large establishments.

In Table 4 we present regression results using more traditional measures of diversity. In particular, we include the percent of workers in the establishments that are white male, minority male, and white female to capture the workforce demographic mix. The percent of workers that are minority female is our excluded group. The results using this more traditional measure of diversity present a less clear picture of how diversity is related to productivity. Looking at the results for manufacturing shows that establishments with a higher percentage of male workers relative to minority female workers are more productive, suggesting that less diverse establishments are more productive. However, the positive association between male workers and productivity is significant for both the percent of white male workers and the percent of minority male workers. While the expected productivity of an establishment with more nonwhite males relative to nonwhite females may be higher, the question remains, is the establishment more diverse?

The problem with these traditional measures is two-fold. First, as mentioned above, measures such as percent white male do not capture how the characteristics of the workforce in an establishment compares to the relevant workforce or labor market. If the representation of minority males on an establishment's payroll is greater than their representation in the relevant comparison pool, one could reasonably argue that reducing the share of minority men on the payroll should increase, not decrease, diversity. Any measure of diversity should be based on a comparison between the characteristics of workers in some unit relative to the relevant base. Second, in these regression estimates, such measures limit “diversity” to a series of pairwise comparisons: minority women vis-à-vis white men, minority women vis-à-vis minority men, minority women vis-à-vis white women.[14] More reasonable, and representative of the concerns of employers, would be to calibrate the relative balance of *all* groups of workers present on the payroll simultaneously. We view these two shortcomings of the traditional measures as being quite serious. It is for these reasons that we devised our alternative measure of diversity, and find the results of Table 2 more illuminating than those of Table 4.

Finally, Table 5 presents our results from estimating equation (1) using log multi-factor productivity as our dependent variable and focusing exclusively on manufacturing establishments. Column (1) presents results using our payroll and occupational diversity measure while column (2) presents results using the traditional diversity measures. As with the results reported in Table 3 for large manufacturing establishments, the estimated relationship between productivity and workforce diversity is stronger here than in Table 2. Looking first at column (1) we see that, after adjusting for differences in capital and materials, both the payroll and occupational diversity measures are positively and significantly related to productivity. Therefore, it appears to be the case that the estimated relationships between payroll diversity and productivity in Table 2 are not due to the fact that we failed to control for cross-establishment differences in capital or materials, at least for manufacturing establishments. The omission of controls for differences in capital or materials does, however, weaken the association between occupational diversity and productivity.

Controlling for cross-establishment differences in capital or materials also affects the estimated relationship between productivity and the presence of older workers as well as the traditional measure of workforce diversity. The coefficients on percent older workers in columns (1) and (2) and the coefficients on the traditional measures of diversity (percent white male workers, percent minority male workers and percent white female workers) in column (2) are not significantly related to productivity after controlling for cross-establishment differences in capital

[14] One could also have omitted white men instead of minority women, which, while more common, does not alter the underlying dichotomous structure of the definition.

and materials. Apparently the significant relationship between these variables and productivity seen in Tables 2, 3 and 4 is a function of failing to control for differences in the use of capital and materials in manufacturing establishments.

Interestingly, after controlling for capital and materials, there remains a positive coefficient on the percent college grad. variable. This may be attributed to the fact that we have not controlled for differences in the cost of labor in these regressions (in equation (1) L_i is measured in hours, not dollars).

V. Conclusion

To examine the relationship between diversity and productivity we use a recently constructed employer-employee matched database, the NWECD, and construct a unique measure of workforce diversity. We find that diversity is either positively associated with establishment-level productivity, or there is no significant relationship between diversity and establishment-level productivity. The empirical weight, however, appears to lean more heavily on the side of a positive association, at least for manufacturing. We never find a significantly negative association between productivity and our measure of diversity. To the extent that governmental affirmative action policies are forcing employers to hire a more diverse workforce, these results suggest that affirmative action policies do not hurt establishment performance. To the extent that firms are voluntarily hiring more diverse workers, these results suggest that it is possible to do so without hurting establishment productivity.

However, there are a number of important caveats to consider. First, we may miss some important costs or benefits that are associated with employing more diverse workers. Previous work suggests that it may be more costly to recruit qualified minority and female workers (Holzer and Neumark, 2000b). In addition, firms may have to spend resources on programs, such as diversity training, in order to successfully incorporate minority and female workers into their workforce. To the extent that we miss these costs, then we may overstate the relationship between diversity and productivity. Alternatively, if one of the main benefits of workplace diversity is an increase in brand loyalty or good will capital on the part of customers—a benefit that is not captured in the current output price—we may understate the relationship between diversity and firm performance. Third, given that the NWECD is a cross-sectional database, we are unable to examine the causal relationship between diversity and productivity. One possible explanation for our findings is that more talented managers achieve a diverse workplace while simultaneously producing more output with the same inputs than less talented managers. Highly productive firms are more diverse, but becoming diverse will not necessarily make a firm highly productive. Finally, again due to data limitations, we are unable to examine how establishments move from having a homogeneous workforce to having a heterogeneous workforce and whether certain management or organizational practices achieve both a diverse and more productive workforce. Clearly, addressing this and the previous limitation requires panel data on establishments, along with data on management practices in the establishment—data we hope to create in the future. For now the results in this paper should be interpreted as being descriptive of the diversity-productivity pattern in manufacturing, retail trade, and service establishments.

Businesses seem to be devoting real resources to promoting (or at least to creating the appearance of promoting) a diverse workforce. A recent survey conducted by the Society of Human Resource Managers found that almost 50 percent of the HR managers surveyed worked for a firm with a diversity program. This leads to two related questions. 1) Why should a firm want to employ a diverse workforce? 2) What effect does employing a diverse workforce have on the performance of the firm? We have provided a number of possible answers to question 1, however, our primary emphasis in this paper has been examining question 2. Our hope is that by examining the effect diversity has on productivity, we will begin to understand why firms may want to employ a diverse workforce. While our results are primarily descriptive, given the lack of existing evidence in this area, we feel that these results provide valuable new insights into the establishment-level relationship between diversity and performance.

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Appendix

Alternative Measurement of Diversity

The alternative measure of diversity described below captures both the multiple dimensions of diversity and measures how that diversity is distributed across occupations within the workplace.

To formalize the desired properties of a diversity index, begin by defining two matrixes. First, a Payroll Diversity matrix, P, that will illustrate the diversity of the workforce as it appears on the payroll (people hired, irrespective of occupation). Second, an Occupational Diversity matrix, O, that will illustrate the diversity of the workforce as it is spread across occupational categories within the establishment. (A table defining all notation appears below).

To begin, assume just two dimensions for diversity, M1 and M2, (these could be race and gender, for example). M1 and M2 are each subdivided into some number of mutually exclusive classifications. X1 and X2 are the respective *number* of sub-classifications within M1 and M2. For example, if M1 is race, X1 could be 3—non-Hispanic white, African American, and Hispanic, or X1 could be 2—non-Hispanic white, and minority. Then P is a matrix of X1*X2 cells. Define D to equal the number of diversity cells in P, or the number of cross-classifications. Thus D=X1*X2. For example, if race and gender are the only two dimensions of diversity, and race is classified as non-Hispanic white and minority, matrix P would have D=4 cells: non-Hispanic white men, minority men, non-Hispanic white women and minority women. Each cell, i, in P contains the proportion of the establishment's workforce (or payroll) that falls into each cross-classification of the dimensions of diversity.

Matrix P for M1=Race, M2=Gender,
X1=2 (non-Hispanic white, minority) and X2=2 (male, female)

M2=gender M1=race	Man	Woman
White	i1= % of workforce that are white men	i2=% of workforce that are white women
Minority	i3=% of workforce that are minority men	i4=% of workforce that are minority women

Now assume some number of occupational categories, say three—Occ1, Occ2, Occ3 (these could be white, blue and pink collar jobs, for example), and define C to be equal to the number of occupational categories. Now O, the Occupational Diversity matrix, is a matrix of L cells, where L=D*C = (X1*X2)*C, or the number of cells in matrix P times the number of occupational categories. As O is defined above, an establishment with just three occupational categories (C=3, where Occ1=blue collar, Occ2=pink collar, and Occ3=white collar) would have L=12 cells, if D=4. Each cell, ij, in O contains the proportion of the establishment workforce that falls into each race, gender, and occupational cell.

Matrix O for D=4 (four diversity cross-classifications from P)
and C=3 (three occupational categories)

	Occ1, j=1 (blue collar)	Occ2, j=2 (pink collar)	Occ3, j=3 (white collar)
White Man, I=1	% of workforce that are white men in Occ 1	% of workforce that are white men in Occ 2	% of workforce that are white men in Occ 3
White Woman, I=2	% of workforce that are white women in Occ 1	% of workforce that are white women in Occ 2	% of workforce that are white women in Occ 3
Minority man, I=3	% of workforce that are minority men in Occ 1	% of workforce that are minority men in Occ 2	% of workforce that are minority men in Occ 3
Minority woman, I=4	% of workforce that are minority women in Occ 1	% of workforce that are minority women in Occ 2	% of workforce that are minority women in Occ 3

In constructing an alternative diversity measure, the following properties are desired:

1. Given some construction of diversity dimensions, M1, M2, etc., and the respective cross-classifications within each dimension, the index should vary directly with the number of cross-classifications actually represented in the workforce. The more non-zero cells in matrix P, the higher the index.
2. Assume there is a baseline population that the establishment's workforce should mirror. Define B_i, to be the representative share in the baseline population of each diversity dimension cross-classification. The index should vary directly with the workforce's proportionate representation of the baseline share for each cell, i, with no increase coming from exceeding the baseline proportion in a given cell, i. For example, if the proportion of white women in the establishment's workforce grows closer to, but does not exceed the proportion of women in the baseline population, the index should increase.
3. The index should vary directly with the occupational spread within each diversity cross-classification. If workers in each diversity cross-classification are more evenly spread across occupations in the establishment, the index should increase. In other words, if two establishments have equal payroll diversity, the diversity index should register greater diversity for the establishment where minority women are better dispersed across occupational categories, all else equal.
4. The index should be flexible, able to incorporate broad or narrow definitions of diversity. It should be able to handle many or few diversity dimensions as well as the number of cross-classifications, i.e., increasing or decreasing D of matrix P.
5. It should be invariant to changes in the total number of workers or occupational categories. Simply refining the occupational categories should not improve the index if workers are not better spread across those jobs.
6. The index should not give a big pay-off to tokenism. Increasing the proportion in a cell of P or O from zero to some small decimal should not cause a large increase in the index.
7. The index should be bounded by zero and one for ease of intuitive interpretation; one indicating perfect diversity, zero indicating no-diversity.

Our alternative measure is defined with these properties in mind. The measure is composed of two terms, one to capture the degree of payroll diversity, the matrix P; the other, the degree of occupational diversity, stemming from matrix O. An index of 1,1 would indicate both perfect payroll diversity (the establishment's payroll perfectly mirrors the diversity of the baseline population) and perfect occupational diversity (the establishment's workers are evenly spread across its occupations in perfect proportion to their representation in the workforce). Term 1 (Payroll Diversity) is defined as follows:

$$\text{Term 1} = \frac{(\sum_{i=1}^{D} Min(\frac{W_i}{B_i},1))-1}{D-1} \tag{A1}$$

where W_i is the proportion of the workforce in each diversity cross-classification cell i,
B_i is the proportion of the baseline population in each diversity cross-classification cell i,
D is the number of cells in the Payroll Diversity matrix.

This term sums the workforce diversity proportions relative to the baseline population proportions across the matrix P. The closer the establishment's workforce proportions are to the baseline population, the better the workforce reflects the baseline, (say the regional workforce diversity mix), and the higher the index. If the workforce over represents any one diversity classification, only one is included in the sum. In other words, the ratio is capped at one. Subtracting 1 from this sum forces the index to equal 1 if the workforce perfectly mirrors the baseline population and zero if there is no diversity. The D-1 term in the denominator is also necessary to force this term to be between 0 and 1, inclusive.

Term 2 (Occupational Diversity) measures how well the diversity present in the establishment's workforce is spread across its occupations. Term 2 is defined as follows:

$$\text{For } E_{ij} \neq 0; \text{Term 2}=\frac{\left[\left(\sum_{i=1}^{D}\sum_{j=1}^{C} Min(\frac{S_{ij}}{E_{ij}},1)\right)-1\right]}{\left[(D*C)-1-Z\right]} \tag{A2}$$

where S_{ij} is the observed proportion of the workforce that belongs to cell i,j, $E_{ij} = Occ_j*W_i$ = the expected proportion of the workforce that belongs to cell *i,j*, *D* is the number of diversity cells in matrix P, *C* is the number of occupational categories, and *Z* is the number of expected cells in matrix O that contain zero—the number of times an occupation contains no workers of a specific diversity cross-classification.

As with term 1, only the minimum of the ratio and 1 is included in the summation. This time the summation is summed over i and j. The ratio is the observed proportions in cell i,j divided by the expected proportions. The observed proportions (S_{ij}) are those actually present in the establishment. The expected proportions (E_{ij}) are what you would expect to find if the workforce were spread evenly across occupations with respect to each diversity cross-classification. It is the product of the proportion of the workforce in occupation j (Occ_j) and the proportion of the workforce in diversity classification i (W_i). This ratio is based on the notion of statistical independence—the expected value is the value that would result if workers were spread across the establishment's given occupational structure independent of their diversity cross-classification.

In words, the numerator of Term 2, calculated only for E_{ij} not equal to zero, is the sum over i (from 1 to D) and j (from 1 to C) of the minimum of 1 and the ratio of the observed to the expected proportions of the workforce that belong to each i,j cell, minus 1. The denominator of Term 2 is the number of cells in the O matrix, minus 1, and minus the number of cells in matrix O for which the expected value is zero. The subtraction of Z (the number of cells in O for which the expected value is zero) in the denominator is required by the restriction that the summation in the numerator be calculated only for E_{ij} not equal zero. The maximum number of terms in the numerator is D*C- Z. Subtracting Z from the denominator assures that the numerator and denominator are computed for the same number of cells. Also, since 1 is subtracted from the numerator to restrict the numerator to values between 0 and 1, inclusive, 1 must also be subtracted in the denominator.

Notation Table for Alternative Diversity Measure

B_i = The baseline share of a diversity cross-classification, e.g., the proportional representation of Hispanic men in the regional workforce.
C = The number of occupations.
D = X1 * X2 = The number of cell in matrix P.

E_{ij} = The expected proportion of establishment's workforce in cell ij of the matrix O. Constructed from the proportion in Occ_j * W_i.

L = D * C = The number of cells in the matrix O.

M1,
M2, etc = Dimensions of diversity, e.g., M1 = race, M2 = gender.
O = Occupational Diversity Matrix.

Occ_j = Occupations in establishment, j = 1 to C.
P = Payroll Diversity Matrix.
S_{ij} = The observed proportion of establishment's workforce in cell ij of the matrix O.

W_I = The proportion of establishment's workforce in diversity cross-classification cell i of the matrix P.

X1 = Number of classifications in diversity dimension M1.

X2 = Number of classifications in diversity dimension M2.

Z = Number of cells for which E_{ij} is zero.

Table 1: Summary Statistics for Establishments in Our Data

	Mean (1)	Std. Dev (2)
Total Employment	216.33	467.52
Log ((Value-Added)/TE)	3.92	1.18
Log (Sales/TE)	4.28	0.93
Percent White Male Workers	0.46	0.30
Percent White Female Workers	0.42	0.30
Percent Minority Male Workers	0.06	0.11
Percent Minority Female Workers	0.06	0.12
Percent College Grad.	0.12	0.14
Percent Workers Over 50	0.19	0.15
Percent of Workers Matched	0.15	0.11
Payroll Diversity	0.39	0.25
Occupational Diversity	0.55	0.18
Number	18,509	

Table 2: Regression of Plant-level Labor Productivity on Plant-level Diversity

	Manufacturing		Services		Retail Sales	
	Log (Value-Added/TE)	Log(Sales/TE)	Log(Value-Added/TE)	Log(Sales/TE)	Log(Value-Added/TE)	Log(Sales/TE)
	(1)	(2)	(3)	(4)	(5)	(6)
Payroll Diversity	0.12	0.11	0.14	0.12	-0.02	-0.03
	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)	(0.04)
Occupational Diversity	0.03	0.04	0.09	0.05	-0.04	-0.05
	(0.04)	(0.03)	(0.05)	(0.04)	(0.06)	(0.05)
Percent Older Workers	-0.08	-0.07	-0.19	-0.09	-0.23	-0.21
	(0.04)	(0.03)	(0.06)	(0.04)	(0.06)	(0.05)
Percent College Grad.	0.33	0.34	0.23	0.26	-0.12	-0.04
	(0.06)	(0.04)	(0.06)	(0.04)	(0.08)	(0.07)
Log (TE)	0.08	0.08	0.08	0.08	0.06	0.08
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Single-Unit	-0.34	-0.27	-0.13	-0.10	-0.03	-0.02
	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)
R-squared	0.58	0.61	0.53	0.62	0.70	0.73
Number	11773	11773	4545	4545	2191	2191

Note: Standard errors in parenthesis. Regressions include controls for four-digit SIC industry and for the four census regions.

Table 3: Regression of Plant-level Labor Productivity on Plant-level Diversity—Large Establishments (establishments with 500 or more employees)

	Manufacturing		Services	
	Log (Value-Added/TE)	Log(Sales/TE)	Log(ValueAdded/TE)	Log(Sales/TE)
	(1)	(2)	(3)	(4)
Payroll Diversity	0.45	0.37	0.17	0.13
	(0.11)	(0.09)	(0.06)	(0.04)
Occupation Diversity	0.58	0.42	0.04	0.06
	(0.24)	(0.19)	(0.15)	(0.09)
Percent Older Workers	-0.77	-0.51	-0.97	-0.16
	(0.25)	(0.20)	(0.23)	(0.14)
Percent College Grad.	0.67	0.70	0.55	0.41
	(0.31)	(0.25)	(0.15)	(0.09)
Log (TE)	0.01	-0.05	-0.03	0.02
	(0.10)	(0.04)	(0.03)	(0.02)
Single-Unit	-0.26	-0.25	-0.04	-0.05
	(0.13)	(0.10)	(0.03)	(0.02)
R-squared	0.71	0.74	0.44	0.40
Number	1032	1032	601	601

Note: Standard errors in parenthesis. Regressions include controls for four-digit SIC industry and for the four census regions.

Table 4: Regression of Plant-level Labor Productivity on Measures of Worker Characteristics

	Manufacturing		Services		Retail Sales	
	Log (Value-Added/TE)	Log(Sales/TE)	Log(Value-Added/TE)	Log(Sales/TE)	Log(Value-Added/TE)	Log(Sales/TE)
	(1)	(2)	(3)	(4)	(5)	(6)
Percent Non-Hispanic	0.48	0.42	-0.06	0.03	0.21	0.19
white Male	(0.07)	(0.06)	(0.08)	(0.06)	(0.09)	(0.08)
Percent Minority Male	0.59	0.50	0.16	0.29	0.33	0.28
	(0.09)	(0.07)	(0.16)	(0.11)	(0.15)	(0.13)
Percent Non-Hispanic	0.12	0.07	-0.02	-0.04	0.07	0.05
white Female	(0.07)	(0.06)	(0.06)	(0.04)	(0.08)	(0.07)
Percent Minority Female	---	---	---	---	---	---
Percent Older Workers	-0.09	-0.08	-0.19	-0.09	-0.23	-0.20
	(0.04)	(0.03)	(0.06)	(0.04)	(0.06)	(0.05)
Percent College Grad.	0.30	0.31	0.26	0.26	-0.15	0.06
	(0.06)	(0.04)	(0.06)	(0.04)	(0.08)	(0.07)
Log (TE)	0.09	0.08	0.09	0.09	0.05	0.08
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Single-Unit	-0.34	-0.27	-0.13	-0.10	-0.03	-0.02
	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)
R-squared	0.59	0.62	0.53	0.62	0.70	0.74
Number	11773	11773	4545	4545	2191	2191

Note: Standard errors in parenthesis. Regressions include controls for four-digit SIC industry and for the four census regions.

Table 5: Regression of Total Factor Productivity (TFP) on Plant-level Diversity—Just Manufacturing Establishments

	Alternative Diversity Measures	Traditional Diversity Measures
	(1)	(2)
Payroll Diversity	0.08	---
	(0.018)	
Occupational Diversity	0.07	---
	(0.021)	
Percent White Male	---	-0.02
		(0.035)
Percent Minority Male	---	-0.01
		(0.047)
Percent White Female	---	-0.01
		(0.036)
Percent Minority Female	---	---
Percent Older Workers	-0.01	-0.01
	(0.021)	(0.022)
Percent College Grad.	0.06	0.07
	(0.027)	(0.027)
Log (TE)	0.02	0.02
	(0.004)	(0.004)
Single-Unit	-0.03	-0.04
	(0.008)	(0.008)
R-squared	0.68	0.68
Number	11043	11043

Note: Standard errors in parenthesis. Regressions include controls for four-digit SIC industry and for the four census regions.