Technology and Firm Size-Wage Differentials in Colombia, Mexico, and Taiwan (China)

Hong Tan and Geeta Batra

In many economies, studies have found large wage differentials not accounted for by workforce characteristics, collective bargaining, or market power. Researchers attribute these differentials to either unobserved worker quality or pay incentives designed to elicit worker effort. This article finds empirical support for an alternative explanation: These wage differentials result from firms' technology-generating activities. Using firm-level data from Colombia, Mexico, and Taiwan (China), the article compares the effects of research and development, worker training, and exports by employers on the wages of skilled and unskilled workers. The results suggest that technology investments lead to large wage premiums for skilled workers but not for unskilled workers. These wage premiums are primarily the result of investments in research and development and in training, while exporting is relatively less important except in Colombia.

Technology plays a vital role in shaping the interfirm structure of wages in developing economies. How do the technology-generating activities of firms—broadly defined to include investments in research and development (R&D), foreign technology and know-how licenses, worker training, and exporting—affect the size structure of wages? Are the effects of these firm investments symmetrical with regard to all workers, or are they biased toward skilled workers as suggested by the skill-biased hypothesis of technical change? Which of these investment activities has the largest effects on wages?

Large differentials in wages paid to ostensibly similar workers characterize labor markets in many industrial and developing economies. For example, studies using household- or individual-level surveys have found sizable wage differentials, even after accounting for a wide range of human capital attributes such as age, sex, and education. These wage differentials appear to vary systematically by employer size and industry, to persist over long periods of time, and to be correlated across countries (Katz and Summers 1989). The enduring nature of these significant, and largely unexplained, wage differentials raises thorny questions about whether labor and product markets are efficient—especially in

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developing economies—and whether policy interventions to improve the operation of these markets are indicated.

Groshen (1991) advanced four hypotheses to explain these wage differentials, each with very different policy implications. Unexplained differentials may (a) reflect quasi-rents from imperfectly competitive markets; (b) compensate for differences in the quality of working conditions; (c) represent wage incentives designed to elicit greater worker effort and reduce shirking; and (d) reflect unmeasured worker quality and skills. To date most studies have found little empirical support for the first two hypotheses, as measured by the degree of unionization, market power of firms, or working conditions in jobs. The last two hypotheses are more difficult to test because of the paucity of relevant worker and firm-level data, and their efficacy in explaining these firm-size and industry wage differentials remains unclear.

A growing body of evidence, primarily from industrial economies, indicates that technological change influences wage inequality. Rising wage inequality in the United States between skilled and unskilled workers has been attributed to skill-biased technology by Katz and Murphy (1992), using time-series labor force surveys, and by Davis and Haltiwanger (1991), using panel firm data. Several recent U.S. studies using direct firm-level measures of technology use or R&D have found corroborating evidence for this hypothesis. Dunne and Schmitz (1995) find that use of advanced manufacturing technology is associated with significant wage differentials, with technology-wage premiums of equal magnitude as firm size-wage premiums. Bernard and Jensen (1994) jointly investigate the roles of exporting and R&D by employers and find evidence that both activities are associated with wage differentials. Similar research on these hypotheses in developing economies is limited; however, using firm-level data from the 1986 Taiwan (China) census, Aw and Batra (1995) find that the average wage premiums associated with exporting were 24 percent.

Research has focused on the linkages between technology and worker training and their consequences for wage growth and wage inequality. Using worker-level data with self-reported training measures, several studies find evidence in industrial economies that the propensity to train is greater for more educated workers, larger firms, and employers in R&D-intensive industries. Furthermore, these studies show higher returns to training in technologically progressive industries (Mincer 1991; Lillard and Tan 1992; Tan and others 1992). Several firm-level studies, exploiting linkages with employee files, have found similar correlations between technology use by employers and wages and worker characteristics (Doms, Dunne, and Troske 1994; Hellerstein, Neumark, and Troske 1994). Because the firm-level studies had no data on worker training, the possibility remains that part of the technology-wage premiums that they estimated—for different firm-worker characteristics—may actually reflect important, but largely unmeasured, employers’ investments in worker training and skill upgrading.

In this article, we bring together unique firm-level data from three developing economies—Colombia, Mexico, and Taiwan (China)—to investigate the rela-
relationships between technology and the interfirm structure of wages in manufacturing. The data for Taiwan (China) are for 1986, and those for Mexico and Colombia are for 1992. Each firm reported information on several key groups of variables: mean wages by level of worker skill, firm and industry characteristics, and the firm’s technology inputs. We hypothesize that firms acquire technological knowledge through three channels: exports, an informal channel to technology and know-how from abroad; investments in new technology, either through foreign licenses or through own R&D efforts; and worker training, which is a critical input in the adoption, modification, and effective use of new technologies.

For each economy, we estimate semiparametric models to characterize the size-wage distributions of two groups of firms differentiated by their technology orientation: firms that invest in one or more of the three channels of technology (investors) and firms that do not invest in any of the three (noninvestors). We compare the firm size-wage distributions of skilled and unskilled workers in investor firms and noninvestor firms to test the hypothesis of skill-biased technical change. It is possible that some sources of technology have a larger impact on wages than others. To identify the relative wage impacts of each of these technology investments, we also estimate separate models for each technology source while controlling for investments in the other two technology sources.

Section I discusses the motivation for the analysis, drawing upon salient findings from our parallel research on training and its effects on firm-level productivity and wages using data from these developing economies. Section II describes the data, provides some descriptive statistics on the firms in our samples, and discusses the econometric model to be estimated. Section III reports the principal findings. Section IV summarizes the cross-economy results and draws out their policy implications.

I. Technology and Wage Differentials

Our analytic approach is motivated by a model in which firms develop technological capabilities through conscious investments in knowledge-generating activities. Firms can develop these capabilities—including own R&D and purchases of foreign technology and know-how, worker training and skill upgrading, as well as exports—in different ways, and each investment strategy may have different productivity and wage outcomes. We focus on estimating the wage outcomes of these technology-generating activities, both jointly and separately by source, and on how these activities shape the size-wage distributions in Colombia, Mexico, and Taiwan (China).

Our definition of technological capability follows Bell and Pavitt (1993). They distinguish between production capacity and technological capability. Production capacity measures the capacity of firms to produce output at given levels of efficiency with existing inputs of capital, labor, and technology. Technological
capability incorporates the additional and distinct resources needed to generate and manage technological change, including specialized managerial and technical skills, knowledge and experience, and linkages with other firms. Employers whose workers have these specific skills and knowledge have a productivity advantage over less capable firms. The firm-specificity of these skills and knowledge creates a bilateral monopoly situation and incentive problems of motivating workers to acquire and exercise specific skills. The bilateral monopoly problem is resolved through firm-worker sharing of the higher productivity (rents) from these technology investments (Becker 1975; Tan and others 1992; Lindbeck and Snower 1989).

We assume that there is a prior distribution of technological capabilities in a given economy at any point in time. The heterogeneity in capabilities and its correlation with firm size have been modeled by Lucas (1978), Jovanovic (1982), and Dunne and Schmitz (1995), among others, in the context of advanced technology use. The Dunne and Schmitz study finds evidence that larger firms are more likely to use advanced technology, that technology usage is related to significant wage differences, and that technology-wage premiums are roughly of the same magnitude as size-wage premiums. In addition, employer incentives to invest in new technology may vary across industries because of interindustry differences in technological possibilities. In science-based industries, such as chemicals and electronics, the potential for product and process innovations is typically greater than in traditional industries such as leather and furniture. These technology differentials can give rise to a distribution of wages across employers, varying the distribution by size and industry—differentials that can persist because of the firm-specificity of technology investments. If technology is the driving force, then similar interindustry differentials are likely to be found across countries.

Tabulations of the data for Colombia, Mexico, and Taiwan (China) indicate that larger firms are typically more likely to train their workers, license foreign know-how, or invest in R&D, while smaller firms tend not to train and to rely on older and less skill-intensive kinds of technology. The data also show systematic differences across industries in the proportion of firms that invest in R&D and training, with the propensity to train workers, conduct R&D, or purchase know-how being higher in the science-intensive industries than in the more traditional, labor-intensive industries.

Technological capabilities can be developed in several ways. First, employers can invest in their own R&D or purchase technology and know-how through licensing agreements with foreign firms. The evidence from developing countries suggests that reverse engineering, imitation, and modification of foreign technology have been more critical to developing capabilities than own investments in basic research and innovation (Pack 1992b). Second, firms can acquire relevant and best-practice technology through their links with foreign buyers of exported products as well as with foreign firms operating in the local markets (Westphal, Rhee, and Pursell 1984; Pack 1992a). Finally, whether it is through
importing foreign technology or using, adapting, and redesigning technology through deliberate investments in R&D, building technological capacity depends fundamentally on the education and training of the workforce. As technologies evolve, a continuous process of job-specific training and retraining is needed to supply the technical and managerial skills required by new process and product innovations.

There is a body of evidence from both industrial and developing countries that technologically progressive industries are more likely to train their workers and that these investments give rise to higher wages (Lillard and Tan 1992; Tan and others 1992). Using census data from Taiwan (China), Aw and Tan (1993) show that worker training has a large positive impact on firm-level productivity in all industries studied and that this effect is larger when training is accompanied by complementary investments in formal R&D and foreign know-how.

Our related research on the productivity effects of enterprise training supports the focus here on elements that are important in developing technological capabilities (see Tan and Batra 1995). First, within a production function framework, our cross-national analyses showed significant firm-level productivity gains from investments in each of the three sources of technology. Our findings of positive productivity effects from R&D and exporting are consistent with those reported in the productivity literature (see Bregman, Fuss, and Regev 1991). The productivity effects of training, however, are new. The results showed that formal training of skilled workers had a significant, positive effect on firm-level productivity, while the productivity effects of unskilled worker training were generally insignificant.

Second, we found that some of the productivity gains from training were shared with workers in the form of higher wages. The results of joint estimation of a production function and wage model showed that the training effects in the wage model were approximately two-thirds those of training in the production function. The implied sharing of productivity gains—one-third to the employer, two-thirds to workers—was of roughly the same magnitude across the three economies. Firm-worker sharing of the costs and returns to training are consistent with the presence of firm-specific training (Becker 1975).

These two findings—the link between investments in technology and firm-level productivity, on the one hand, and the link between productivity and wages, on the other—constitute the empirical basis for this article. We build on these findings to investigate the firm size-wage distribution across different groups of firms varying in technological orientation, by skill level, and across economies.

II. DATA AND METHODOLOGY

The data required to investigate the hypothesized technology-wage relationships are available for a cross-section of firms in the three economies—Colom-
bia, with 500 firms for 1992; Mexico, with 5,072 firms for 1992; and Taiwan (China), with 8,408 firms for 1986.¹ The three surveys of manufacturing firms contain broadly comparable, firm-level information on the key variables of interest. These include characteristics of the establishment, including year established, single-plant or multiplant status, two-digit industry classification, and foreign ownership; data on production and inputs, including capital assets, employment, intermediate inputs, and energy use; number of workers and mean wages by broad occupations; and information on exports, training, and expenditures on \textit{R\&D} and foreign technology licenses.

\textit{Variable Definitions}

"Training" is defined to include only formal structured training provided by the employer, whether by in-house trainers or by external providers, but excludes informal on-the-job training provided either by coworkers or by supervisors. A more inclusive training variable would have little discriminatory power because most employers provide some informal on-the-job training, especially to new hires. The decision to exclude informal on-the-job training was informed by the findings of existing training studies (for example, see Lillard and Tan 1992) and by our own analyses of the productivity effects of different types of formal and informal training (see Tan and Batra 1995). The training variable is based on the number of employees trained by each source, except in Taiwan (China) where it is defined by positive expenditures on (presumably formal) training. Training in the Taiwan (China) sample, in all likelihood, is understated by our reliance on reported training expenditures, which are often not adequately recorded, rather than on the number of workers trained where better data are available. Thus more training firms in Taiwan (China) are probably misclassified as nontrainers than in the other two countries. For the Taiwan (China) analysis, this is likely to cause a downward bias in the estimated effects of training on wages, which strengthens our test for the presence of training-wage premiums.

The variable "investment in \textit{R\&D} and know-how" is defined as positive expenditures on either research and development or on the purchase of foreign technology and know-how licenses. We note that \textit{R\&D} is defined more broadly in Mexico and Colombia than in Taiwan (China) and includes less-formal, adaptive \textit{R\&D} and engineering modifications to product and process technologies. The variable "exports" is defined simply as having positive foreign exports. We will refer to these three variables as sources of technology and use them to separate firms into two groups, investors and noninvestors. Investors invest in

¹ We exclude \textit{maquiladora} firms from the Mexico sample because of the their unique, assembly-for-export characteristics. These firms, although typically large, conduct virtually no \textit{R\&D} and generally pay lower wages to both skilled and unskilled labor. Although they were not explicitly identified in our sample, we defined \textit{maquiladora} firms as those that export 67 percent or more of their total output and import 75 percent or more of their raw materials. Thus, we dropped 305 firms from the analysis. We acknowledge Amy Hwang (Academia Sinica) for providing the data for Taiwan (China); the Secretariat of Labor (Mexico) for providing the data for Mexico; and SENA, the National Training Agency, for the data for Colombia.
any one, or more, of the three sources of technology. Noninvestors do not invest in any of them. We chose this simple stratification to facilitate comparisons between investors and noninvestors and between the three technology sources and to ensure that the sample size for different groups was adequate for analysis. In the simple stratification, a firm is defined as an investor by one of seven combinations of investments in any one or more of the three dichotomous technology indicators. The number of investor permutations rises quickly when each indicator variable is stratified by intensity, making the analysis intractable because of small sample sizes in each investor category. However, we do report some findings for a more disaggregated stratification of firms by intensity of their technology investments.

For each economy, we construct comparable definitions of skilled and unskilled workers using information on the broad occupational breakdowns of the workforce in the firm. For Taiwan (China), the group of skilled workers includes managers, engineers, and technicians; for Mexico, it includes directors, professionals, engineers, supervisors, and technicians; for Colombia, it includes administrators, technicians, and supervisors. Unskilled workers in all three economies comprise unskilled production workers and employees in the residual "other administrative” group. This breakdown of skills is an improvement over the more commonly used breakdown between production and nonproduction workers. For Colombia and Mexico, but not Taiwan (China), we also have information on the educational distribution of workers in the firm. We have not used these data here in the interest of cross-national comparability, but education is partly reflected in our refined measures of skills.

Our wage variable is defined as monthly wages and salaries. It excludes fringe benefits and other nonwage payments because these data, while reported, are for the workforce as a whole and are not broken down by occupational group. In Taiwan (China), nonwage payments for the investor sample are on average 40 percent higher than those for noninvestors. In Mexico, the different bonuses for which we have data—for example, productivity, quality, and punctuality bonuses—are also on average higher among technology investors than among noninvestors and rise with firm size. Thus, inclusion of fringe benefits, bonuses, and other nonwage payments should result in higher technology-wage premiums in these economies and reinforce our findings.

**Overview of the Data**

In all three surveys, large firms were oversampled relative to their true weight in the population of industrial enterprises. The population of smaller firms, microenterprises in particular, is not known with any precision in Colombia and Mexico. A further complication is that the Taiwan (China) sample was selected on the basis of sales. Although crude population weights exist for Colombia and Mexico, we have opted to report only unweighted figures until more comparable weights can be developed for all three countries.
Table 1. Mean Characteristics of Sample Firms in Colombia, Mexico, and Taiwan (China), by Technology Source

<table>
<thead>
<tr>
<th>Economy</th>
<th>Number of firms</th>
<th>Number of employees</th>
<th>Percentage of firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Formal training</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>R&amp;D licenses</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Exporting</td>
</tr>
<tr>
<td>Colombia</td>
<td>500</td>
<td>186.00</td>
<td>65.60</td>
</tr>
<tr>
<td>Mexico</td>
<td>5,072</td>
<td>297.81</td>
<td>56.77</td>
</tr>
<tr>
<td>Taiwan (China)</td>
<td>8,408</td>
<td>145.47</td>
<td>15.84</td>
</tr>
</tbody>
</table>

Table 1 indicates that the average firm size is about 298 employees in Mexico, 186 employees in Colombia, and 145 employees in Taiwan (China). Given the over-representation of large firms, these statistics cannot (and should not) be used to draw inferences about the relative level of technology orientation in the three economies. With this caveat, the remaining columns of table 1 show the percentage of firms in each economy reporting formal training, investments in R&D and technology licenses, and exports.

Table 2 shows the mean characteristics of firms by their technology orientation. In all three economies, in comparison with noninvestors, firms that invest in any of the sources of technology tend to be larger (in terms of employment) and older (they have been in operation longer), have multiple plants and a higher proportion of foreign capital, and pay higher wages to both their skilled and unskilled employees. Given the stylized finding of a firm size-wage relationship in most economies, part of the higher wages paid by investors in technology (or any source of technology) reflects their larger average size. In the analysis that follows, this firm size-wage relationship is explicitly modeled in estimating the technology-wage premium; interindustry differences are accommodated by a vector of two-digit industry dummy variables, but these are not the focus here.

**Empirical Methodology**

The impact of technology on industrial wage differentials is investigated in several ways. First, we compare the wage distributions of the two groups of firms that differ in their technology orientation and test the hypothesis that, other things being equal, technology investors pay higher wages. Employer size is a useful way to characterize this distribution of wages because technological capability is thought to be a positive function of firm size. Second, the wage comparisons are done separately for skilled and unskilled workers. If technological change is highly skill-demanding, as suggested by the literature, then employer investments in technology should have a larger wage impact on skilled workers relative to unskilled workers. Finally, we estimate the separate wage effects of employer investments in exporting, worker training, and R&D to see which technology strategy has the largest impact on wages and whether there are major differences across economies in the role of each technology source.
Table 2. Mean Characteristics of Sample Firms in Colombia, Mexico, and Taiwan (China), by Technology Orientation

<table>
<thead>
<tr>
<th>Economy and technology orientation</th>
<th>Number of employees</th>
<th>Years in operation</th>
<th>Multiple plants (percentage of firms)</th>
<th>Foreign ownership (percentage of firms)</th>
<th>Percentage of skilled labor</th>
<th>Ratio of wages paid by investors to those paid by noninvestors</th>
<th>Ratio of wages paid to skilled workers to those paid to unskilled workers</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Colombia</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investors</td>
<td>203</td>
<td>20.82</td>
<td>20.31</td>
<td>—</td>
<td>0.23</td>
<td>2.36</td>
<td>2.69</td>
</tr>
<tr>
<td>Noninvestors</td>
<td>43</td>
<td>14.52</td>
<td>3.85</td>
<td>—</td>
<td>0.24</td>
<td>n.a.</td>
<td>n.a.</td>
</tr>
<tr>
<td><strong>Mexico</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investors</td>
<td>349</td>
<td>23.99</td>
<td>22.74</td>
<td>18.97</td>
<td>0.31</td>
<td>1.30</td>
<td>1.26</td>
</tr>
<tr>
<td>Noninvestors</td>
<td>130</td>
<td>18.74</td>
<td>11.72</td>
<td>6.67</td>
<td>0.29</td>
<td>n.a.</td>
<td>n.a.</td>
</tr>
<tr>
<td><strong>Taiwan (China)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investors</td>
<td>227</td>
<td>12.68</td>
<td>33.69</td>
<td>11.03</td>
<td>0.49</td>
<td>1.34</td>
<td>1.21</td>
</tr>
<tr>
<td>Noninvestors</td>
<td>31</td>
<td>10.76</td>
<td>13.06</td>
<td>1.52</td>
<td>0.55</td>
<td>n.a.</td>
<td>n.a.</td>
</tr>
</tbody>
</table>

— Not available.

n.a. Not applicable.

Note: Investors are defined as firms reporting investments in R&D or formal training (internal or external) or export.

Source: Authors’ calculations.
These wage comparisons are based on nonparametric and semiparametric regression methods (Robinson 1988; Hardle 1990). In initial data exploration, we found the firm-level wage data to have a lot of noise and the size-wage distributions to be nonlinear. In preliminary analyses, we compared wage models estimated by ordinary least squares (OLS) and nonparametric methods in each of the three economies and concluded that the size distribution of wages was better estimated by nonlinear methods. Although the OLS parameter estimates are broadly comparable to the nonparametric estimates for wage intercept differences between investors and noninvestors, and for other explanatory variables such as industry and firm characteristics, they differ markedly in estimates of the size-wage distribution. The OLS quadratic size specification yields poor results because of its sensitivity to noise, nonlinearities, and outliers.

Thus we adopted a more flexible approach. Unlike the more familiar linear regression technique, the wage models we estimate impose no specific functional form on the data, such as a quadratic firm-size specification, in effect allowing the data to speak for themselves. Deaton (1989) discusses these and other advantages of nonparametric techniques over alternative, more familiar econometric techniques such as cross-tabulations, which are not very flexible and do not convey information as transparently, and linear regressions, which tend to oversummarize and rarely do justice to the amount of information available. The semiparametric model extends this methodology by combining a parametric component with the nonparametric one. We let the nonparametric component be related to firm size and the parametric component be a function of other firm attributes, such as age of the firm, multiplant status, foreign capital ownership, and industry. The semiparametric approach thus enables us to compare the within-industry, firm size-wage distributions of technology investors and noninvestors net of the wage effects of other firm-specific factors and cross-industry wage-level differentials.

The semiparametric wage model has the following form:

\[
y = x'\beta + \theta(z) + u
\]

where \( y \) represents the dependent variable, \( \log(\text{wage}) \), \( \beta \) is assumed to be a linear function of \( x \), a matrix of firm attributes including foreign ownership, firm age, multiplant status, and industry. The nonparametric component, firm size, is represented by \( z \), measured as \( \log(\text{employment}) \), and \( u \), the error term, is assumed to be independently and identically distributed with finite variance.

The estimation is done in two stages. In the first stage, we obtain the coefficients of \( x \), that is, \( \beta \), using a kernel nonparametric method and a smoothing parameter designed to minimize the sum of squared residuals (described in greater detail in the appendix). In the second stage, to obtain the relationship between wages and firm size net of the wage effects of other firm and industry characteristics, we estimate the following nonparametric model

\[
y - x'\beta = \theta(z)
\]
where, as before, $y$ is log (wage), $x'\beta$ is a vector of predicted values obtained from the first-stage estimation, $z$ is firm size as measured by log (employment), and $\Theta$ is the function relating wages to firm size.

We estimate a semiparametric wage model for each group of firms, the technology investors and noninvestors samples, and, within each firm sample, separate regressions for skilled workers and for unskilled workers. Because we have already controlled for the wage effects of $x'\beta$, differentials in the size distribution of wages between the two groups of firms are attributed to employer investments in exports, training, or R&D and know-how. Wage differentials for the two skill groups can also be compared to test the hypothesis of skill-biased technological change.

We extend this semiparametric methodology to estimate the separate wage effects of each technology source. Recall that firms are classified as being in the investor sample if they do one or more of the following: exports, training, or R&D and know-how. For any given technology source, we estimate the semiparametric wage model for that group of investors, controlling for the wage effects of contemporaneous investments in the other two technology sources. For example, to estimate the wage effects of training, we expand $x'\beta$ to include two dummy variables—for exporting and for R&D and know-how—so that $\Theta(z)$ provides an estimate of the pure size-wage effects from training. (This procedure ignores second-order, and possibly important, interaction effects between training and the other two technology sources.)

**III. Empirical Findings**

The first set of regressions compares the wages paid by technology investors and by noninvestor firms. We first report the parametric component of wages—firm characteristics and industry effects. We then present graphical comparisons of the nonparametric wage component, the firm size-wage distributions by skill group, for the investor and noninvestor samples. The second set of regressions disaggregates these results by technology source—exports, worker training, and investments in R&D and know-how. For brevity, the discussion here focuses only on the size-wage distributions net of the parametric wage component.  

**Technology Investors and Noninvestors**

Table 3 reports the semiparametric coefficient estimates for the wage effects of different firm-level characteristics, separately by the technology orientation of firms and by skilled and unskilled worker groups. These estimates hold constant interindustry wage-level differentials; these are discussed subsequently.

Table 3 highlights what appear to be common correlates of firm-level productivity across all three economies. First, firm age is generally associated with a
Table 3. Estimates of the Impact of Firm Characteristics on Wages in Colombia, Mexico, and Taiwan (China)

<table>
<thead>
<tr>
<th>Economy and technology orientation</th>
<th>Skilled labor</th>
<th>Unskilled labor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Years in operation</td>
<td>Multiple plants</td>
</tr>
<tr>
<td><strong>Colombia</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investors</td>
<td>0.002</td>
<td>0.103*</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Noninvestors</td>
<td>0.003</td>
<td>0.188</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.225)</td>
</tr>
<tr>
<td><strong>Mexico</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investors</td>
<td>0.067***</td>
<td>0.189***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Noninvestors</td>
<td>0.003*</td>
<td>0.096</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.085)</td>
</tr>
<tr>
<td><strong>Taiwan (China)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investors</td>
<td>0.006***</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Noninvestors</td>
<td>0.007***</td>
<td>0.094***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.026)</td>
</tr>
</tbody>
</table>

— Not available.

* Significant at 10 percent.
** Significant at 5 percent.
*** Significant at 1 percent.

Source: Authors' calculations.

positive and statistically significant effect on wages, except in Colombia. This finding is consistent with the interpretation that longevity is correlated with firm-level productivity, because less efficient firms have a greater likelihood of exit (Jovanovic 1982). Second, foreign ownership is associated with significantly higher wages in Mexico and Taiwan (China) (this variable was not collected for Colombia), possibly because of their higher technological capabilities. (See Tan and Batra 1995 for cross-country findings on the productivity differentials associated with foreign ownership of firms.) Finally, multiplant status is associated with higher wages, but its statistical significance is mixed. Several U.S. establishment-level studies find large multiplant wage effects; the mixed results reported here may simply reflect the fact that our unit of observation is the firm, not the establishment, and that firm-size effects (for which multiplant status is a proxy) are captured in the nonparametric wage component.

Industry dummy variables were also included in the semiparametric wage models to control for interindustry wage differentials. Though not reported here, industry intercepts estimated in each regression suggest that two findings are common to all three economies. First, there appear to be two distinct groups of industries: industries that pay high wages (typically chemicals, pharmaceuticals, general and electrical machinery, basic metals, and transportation equipment) and industries that pay low wages (usually food and beverages, clothing and
The similarities of these two findings across economies are consistent with the hypotheses of interindustry differences in technological possibilities and their associated differential demand for skilled workers. The findings raise questions about the efficacy of more traditional explanations that relate industry wage differentials to market structure, openness to trade, and unionization. We did not explicitly address these competing explanations, given the limited two-digit industry variation in our data, but we argue that cross-national variations in these factors could not give rise to the common patterns of interindustry wage differentials observed.

The Size Distribution of Wages

Our estimates of the nonparametric wage components show the size-wage distributions net of the parametric wage effects reported above. At any given firm size, the gap between the two curves for technology investors and noninvestors is a measure of the percentage wage differential between the two groups of firms. Because investors and noninvestors differ only in whether they invest in any technology, this wage gap is an estimate of the technology-wage premium.

To facilitate comparisons by firm size, we adopt the following firm-size nomenclature for all economies. We define firms with less than 16 employees as micro, firms with 16 to 100 employees as small, firms with 101 to 250 employees as medium, and firms with more than 250 employees as large. We use these definitions to report average wage premiums by discrete firm-size categories.

Figure 1 presents our estimates of the size-wage distributions for Mexico. The wages paid to skilled workers are everywhere higher in firms that invest in technology than in those that do not; furthermore, the wage differential is largest for technology investors in the smaller firm-size range. Compared with the wage premiums paid by noninvestors, those paid by micro, small, medium, and large firms that invest in technology are 88, 33, 32, and 21 percent, respectively.

The corresponding size-wage distributions for unskilled workers are not well differentiated by the technology orientation of firms. For the smallest and biggest firms, wages paid to unskilled workers by technology investors are slightly higher than those paid by noninvestors. The reverse is true for medium-size and larger firms—investors pay slightly lower wages to unskilled workers as compared with noninvestors. By discrete size categories, the technology-wage premiums paid by investors relative to noninvestors are 13, −4, −1, and 1 percent for micro, small, medium, and large firms, respectively.

Figures 2 and 3 show the corresponding size-wage distributions for Taiwan (China) and Colombia, respectively. For skilled workers, the size-wage
Figure 1. *Estimates of the Size-Wage Distributions for Skilled and Unskilled Labor, Mexico*

**Skilled labor**

Mean wage (log)

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<table>
<thead>
<tr>
<th>Mean number of employees (log)</th>
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<tbody>
<tr>
<td>5.5</td>
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<td>8.5</td>
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- O Noninvestors
- O Investors

**Unskilled labor**

Mean wage (log)

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<th>Mean number of employees (log)</th>
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<td>5.5</td>
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<td>8.5</td>
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- O Noninvestors
- O Investors

Source: Authors' calculations.
Figure 2. Estimates of the Size-Wage Distributions for Skilled and Unskilled Labor, Taiwan (China)

**Skilled labor**

Mean wage (log)

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<tr>
<th>Mean number of employees (log)</th>
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<tbody>
<tr>
<td>12.2</td>
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<td>11.4</td>
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- Noninvestors
- Investors

**Unskilled labor**

Mean wage (log)

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<tr>
<th>Mean number of employees (log)</th>
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<td>12.2</td>
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<td>12.0</td>
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<tr>
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<td>11.6</td>
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<tr>
<td>11.4</td>
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<tr>
<td>11.2</td>
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- Noninvestors
- Investors

Source: Authors' calculations.
Figure 3. Estimates of the Size-Wage Distributions for Skilled and Unskilled Labor, Colombia

**Skilled labor**

<table>
<thead>
<tr>
<th>Mean wage (log)</th>
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<tr>
<td>13.5</td>
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<td>13.0</td>
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- Noninvestors
- Investors

**Unskilled labor**

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<tr>
<td>11.5</td>
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<tr>
<td>11.0</td>
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</tbody>
</table>

- Noninvestors
- Investors

Source: Authors' calculations.
distributions in Taiwan (China) and Colombia resemble those in Mexico in being higher for technology investors than for noninvestors. However, each of these economies has slightly different patterns of technology-wage premiums by firm size. For Taiwan (China) (figure 2), the technology premium for skilled workers is highest in the small size category, and the premiums decline with firm size as in Mexico. The technology-wage premiums for skilled workers in Taiwan (China) are 8, 21, 15, and 14 percent in micro, small, medium, and large firms, respectively. For Colombia (figure 3), by contrast, the technology-wage premiums for skilled workers tend to rise with size (except for the largest firms); the corresponding wage premiums by size are 20, 34, 48, and -22 percent, respectively.

For unskilled workers, technology investors in Taiwan (China) and Colombia—as their Mexican counterparts—pay smaller wage premiums for unskilled workers than for skilled workers. In Taiwan (China), there is no systematic pattern by firm size—the mean wage premiums by size are -7, 3, -3, and 0 percent for micro, small, medium, and large firms, respectively. In Colombia the firm-size pattern of technology premiums for unskilled workers resembles that for skilled workers. The corresponding premiums by size are 19, 22, 26, and -13 percent for micro, small, medium, and large firms, respectively.

Technology-wage premiums are averages across all investor firms, irrespective of the intensity of their investments. To verify that the wage effects of technology increase in proportion to investment intensity, we estimated pooled OLS wage models with indicator variables for two intensity levels—moderate and high—measured relative to noninvestors. This OLS wage model has the same variable specification as the nonparametric model except for the inclusion of a quadratic firm-size measure and indicator variables for moderate and high-intensity investors. (This wage model was estimated for Mexico and Taiwan (China), but not Colombia, where small sample size precluded this disaggregation.) A firm is defined to be a high-intensity investor if it invests more than the median intensity in any one of the three technology sources; otherwise it is a moderate investor. The OLS estimates suggest that high-intensity investors pay significantly higher wages than moderate-intensity investors, and both investor groups pay higher wages compared with noninvestors. The results also suggest that technology-wage differentials are larger among skilled workers than unskilled workers. Both results are consistent with our nonparametric findings and reinforce our interpretation of these wage differentials.

To summarize, the results for all three economies provide evidence of large technology-wage premiums for skilled workers, and small or nonexistent technology-wage premiums for unskilled workers (table 4). (We tested, and rejected, the null hypothesis that the wages of skilled workers are the same in investor and noninvestor firms across all size categories.) In Mexico the overall (pooling across firm sizes) technology-wage premium for skilled workers is 54 percent, which is substantial, but the premium for unskilled workers is just 11 percent. In Taiwan (China) the corresponding overall premiums for skilled and unskilled
Table 4. The Technology-Wage Premium by Labor Type in Colombia, Mexico, and Taiwan (China) (percent)

<table>
<thead>
<tr>
<th>Economy</th>
<th>Skilled labor</th>
<th></th>
<th></th>
<th>Unskilled labor</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Training</td>
<td>R&amp;D</td>
<td>Exports</td>
<td>Any investment</td>
<td>Training</td>
<td>R&amp;D</td>
</tr>
<tr>
<td>Colombia</td>
<td>39.93</td>
<td>24.23</td>
<td>61.12</td>
<td>41.76</td>
<td>20.20</td>
<td>8.65</td>
</tr>
<tr>
<td>Mexico</td>
<td>76.12</td>
<td>74.54</td>
<td>51.29</td>
<td>53.88</td>
<td>17.82</td>
<td>12.75</td>
</tr>
<tr>
<td>Taiwan (China)</td>
<td>53.88</td>
<td>51.13</td>
<td>22.38</td>
<td>31.92</td>
<td>14.91</td>
<td>16.77</td>
</tr>
</tbody>
</table>

Note: Values are based on semiparametric regression results. Technology premium is defined as the overall difference between the average wage of firms investing in any source of technology and the average wage paid by noninvestors. The wage premiums for each technology source (training, R&D, exports) are estimated controlling for investments in the other sources of technology.

Source: Authors' calculations.
workers are 32 and 7 percent, respectively; in Colombia the skilled and unskilled technology-wage premiums are 42 and 23 percent, respectively.

We interpret these results as evidence of skill-biased technological change. We note that the same findings are also consistent with skill-neutrality if two assumptions hold: that technology raises the productivity of skilled and unskilled workers to the same degree and that skilled workers are not mobile across firms (so wage premiums can persist), while unskilled workers are mobile and readily substitutable for each other (thus competing away wage differentials). However, we discount this competing explanation on the basis of two findings from our related research (Tan and Batra 1995). First, there is strong cross-national evidence that training for skilled workers has a large productivity impact, but training for unskilled workers does not. Second, although skilled workers are generally less mobile than unskilled workers, the evidence suggests that technically efficient firms, which are highly correlated with our investor firms, have lower job turnover rates among employees than inefficient firms, which make few technology investments.

Size-Wage Distributions by Technology Source

Which technology source has the largest impact on the size distribution of wages? To address this issue, we estimate semiparametric wage regressions separately for samples of firms investing in each of the three technology sources, controlling for their contemporaneous investments in the two remaining technology sources. The sample size used for each technology source varies depending on the specific source under consideration. The resulting firm size-wage distributions are compared with those of noninvestors, yielding estimates of the technology-wage premiums attributable to specific sources of technology.

Figure 4 summarizes the wage premiums for each economy by technology source and by firm size for skilled and unskilled labor. At the broadest level—the case of overall technology wage premiums—the wage premiums estimated for each technology source replicate the principal results from the aggregate measure of technology orientation. Even disaggregating by technology source, wage premiums are greater for skilled workers than for unskilled workers in all three economies. Furthermore, economy-specific patterns of technology-wage premiums by firm size remain—wage premiums are largest for the smallest size category in Mexico; they tend to rise with size (except for the largest firms) in Colombia; and they are highest in the small size category in Taiwan (China), though these size-related wage differentials are not striking. Finally, figure 4 shows that the relative importance of the three technology sources does not vary with size.

Several new results emerge when the wage premiums from each source are considered separately. First, for Mexico and Taiwan (China), table 4 shows that firm investments in R&D and worker training are the principal drivers of the

3. We acknowledge an anonymous referee for drawing our attention to this possibility.
Figure 4. Wage Premiums by Technology Source and Firm Size, Colombia, Mexico, and Taiwan (China)

Note: Micro firms have fewer than 16 employees, small firms have 16 to 100, medium firms have 101 to 250, and large firms have more than 250.

Source: Authors' calculations.
wage premiums paid to skilled workers by technology investors; exporting, as an informal source of technology, is relatively less important. In Mexico, compared with wages paid by noninvestors, employer investments in training are associated with a skilled worker wage premium of 76 percent, R&D and know-how investments with a premium of 74 percent, and exporting with a premium of 51 percent. In Taiwan (China) the corresponding skill wage premiums for worker training, R&D, and exports are lower—54, 51, and 22 percent, respectively—possibly because of higher levels of human capital and knowledge investments in Taiwan (China) than in Mexico. For unskilled workers the corresponding average wage premiums for worker training, R&D, and exports are 18, 13, and −2 percent, respectively, for Mexico, and 15, 17, and 2 percent, respectively, for Taiwan (China).

In Colombia, by contrast, the skill wage premiums for training or for R&D and know-how—40 and 24 percent, respectively—are dwarfed by the skill wage premiums from exporting of 61 percent. This relative ranking of the wage premiums by source persists for the unskilled worker group as well—20, 9, and 29 percent for training, R&D, and exports, respectively—though clearly the size of these premiums is smaller. We suspect that part of the explanation for the relative importance of exports lies in the high protection afforded Colombian industry, at least until recently, as compared with the relatively more open economies of Taiwan (China) and Mexico. In such a protected environment, a firm’s contacts with foreign buyers and suppliers may be a more important source of best-practice technology than own R&D or training.

IV. CONCLUSIONS AND POLICY IMPLICATIONS

Unique firm-level data were used to investigate the structure of industrial wages and the role of technology in giving rise to wage differentials across firms in Colombia, Mexico, and Taiwan (China). Semiparametric methods provided a flexible tool for estimating the size distribution of wages and for disentangling the separate contributions of R&D, training, and exports on the size-wage relationship. The following findings and policy implications emerged from our cross-economy analyses.

Our cross-economy comparisons yielded two principal results. First, controlling for firm characteristics and industry, we found evidence in all three economies that firm investments in technology have a large impact on the size-wage distributions for skilled workers and a relatively smaller impact on wages paid to unskilled workers. This asymmetric wage impact of technology is consistent with the hypothesis of skill-biased technical change. Second, a decomposition of wage effects by source of technology revealed that the wage premiums paid to skilled workers are driven primarily by firm investments in R&D and training; exporting is relatively less important.

The results suggest that the large firm-size wage differentials commonly observed in many economies are primarily the outcomes of employer investments
in technology. In the extant literature, many analysts have speculated that the size and persistence of these wage differentials reflect monopoly rents from market power and imperfections in the labor market, unobserved worker attributes, or incentive wage schemes. Our findings indicate that these wage differentials reflect the returns to firm investments in technology; as such, they do not call for remedial policies to improve the working of labor markets. Though not the focus of this article, we also found large interindustry wage differentials that may reflect industry differences in technological change; this is a fruitful area for future research.

The findings also highlight striking similarities across the three economies in the wage effects of technology investments—sizable wage premiums for skilled workers, but not for unskilled workers. Compared with noninvestor firms, the overall wage premiums for skilled workers are 32 percent in Taiwan (China), 54 percent in Mexico, and 42 percent in Colombia (table 4). In contrast, the corresponding wage premiums for unskilled workers are just 7, 11, and 22 percent, respectively. This result by skill group continues to hold when the separate sources of technology—R&D, training, and exports—are considered. These differential wage effects by skill level mirror the productivity effects of training estimated within a production function framework for the same sample of firms in the three economies. We conclude that technological change is skill biased. The implication is that sustained future economic growth and technological change will depend critically upon an increased availability of educated and skilled workers.

This technology-skill complementarity also has implications for income inequality. For many developing economies, several recent trends—the accelerating pace of best practice in information and industrial technology, the increased inflows of capital and technology, and the growing integration into world markets—could create strong demand for skilled workers far outstripping the supply capacity of their educational and training institutions. Without appropriate responses from the private sector and governments, the outcome is likely to be growing income inequality between skilled and unskilled workers and between those with more and less education.

APPENDIX. SEMIPARAMETRIC AND KERNEL NONPARAMETRIC ESTIMATION

Semiparametric Regression Estimation

The semiparametric regression model has the following functional form:

\[(A-1) \quad y = x'\beta + \theta(z) + u\]

where \(y\) is an \(n \times 1\) vector representing the dependent variable, and \(n\) indexes firms in the sample; \(\beta\) is assumed to be a linear function of \(x\), an \(n \times k\) matrix of \(k\) firm attributes. The nonparametric component is represented by an \(n \times 1\) vector, \(z\). We assume that the error term \(u\) is independently and identically dis-
tributed with finite variance. In addition, \( E(\mu/z, x) = 0 \) and \( \theta \) is an unknown function of \( z \).

Since \( E(y/z) = E(x/z)'\beta + \theta(z) \), equation A-1 can be rewritten as

\[
A-2 \quad y = E(y/z) + (x - E(x/z))'\beta + u
\]

where the deterministic part of \( y \) is decomposed into two parts: one is the effect on \( y \) of \( z \), \( E(y/z) \), and the other is the effect on \( y \) of \( x \) net of \( z \), \( [x - E(x/z)]'\beta \).

To obtain the coefficients of \( x \), that is, \( \beta \), we estimate \( E(y/z) \) and \( E(x/z) \) using a kernel nonparametric method and a smoothing parameter designed to minimize the sum of squared residuals as described below.

**Kernel Nonparametric Estimation**

Given the data base \( \{(Y_i, Z_i)\}_{i=1}^n \), the nonparametric estimate of \( m(z) \) is calculated as a weighted average of \( g(Y_i) \), where the heavier weights are given to the observations with the \( z_i \) closest to \( z \). That is, \( m(z) \) is estimated by

\[
A-3 \quad \hat{m}(z_j) = \frac{\sum_{i=1}^n g(Y_i)W(z, z_i)}{\sum_{i=1}^n W(z, z_i)}
\]

where \( \{W(z, z_i), i = 1, \ldots, n\} \) is a sequence of weights that sums to 1. The idea is that the observations, the \( g(Y_i) \)s, with the \( z_i \) close to \( z \), contain more information on \( m(z) \) than observations far away from \( z \).

The weights can be expressed as

\[
A-4 \quad W(z, z_i) = K(z - z_i) / h / \sum_i (K(z - z_i) / h).
\]

The weighting function expressed in equation A-4 will sum to 1 for all \( z \). \( K(z - z_i)/h \) is called the Kernel function given by \( N^{-1}(z, h) \). \( h \) is a positive scalar bandwidth number or smoothing parameter that determines the weights to be assigned to observations in the neighborhood of \( z \) (Hardle 1990; Delgado and Robinson 1992).

The choice of the smoothing parameter, \( h \), plays an important role in nonparametric regression estimations, because it affects the magnitude of the weights assigned to observations in the neighborhood of \( z \). For example, if \( h \) is too large, the observations far from \( z \) will have a large impact on the \( E(y/z) \). Although it is common practice to assume an exogenous smoothing parameter, it is important that the smoothing parameter depends on the data with a view to reflecting sample size and scale of measurement. We determine the optimal smoothing parameter using least squares cross-validation techniques to determine the optimal bandwidth that gives the best fit of the nonparametrically estimated regression curve to the actual data (Hardle 1990).

**References**

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