SKILL-BASED TECHNOLOGY ADOPTION: FIRM-LEVEL EVIDENCE FROM BRAZIL AND INDIA

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Skill-biased technology adoption: Firm-level evidence from Brazil and India[1]

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Abstract

This paper provides the first firm-level econometric evidence on the skill-bias of ICT in developing countries using a unique new dataset of manufacturing firms in Brazil and India. I use detailed information on firms' adoption of ICT and the educational composition of their workforce to estimate skill-share equations in levels and long differences. The results are strongly suggestive of skill-biased ICT adoption, with ICT able to explain up to a third of the average increase in the share of skilled workers in Brazil and up to one half in India. I then use variation in the relative supply of skilled workers across states within each country to identify the skill-bias of ICT. The results are again consistent with skill-bias in both countries, and are mainly robust to various methods of controlling for unobserved heterogeneity across states. The magnitudes of the estimated effects from both approaches are surprisingly similar for the two countries. Overall, the results suggest that new developments in ICT are diffusing rapidly through the manufacturing sectors of both Brazil and India, with similar implications for the demand for skills in two very different and geographically distant countries. This evidence is consistent with ongoing pervasive skill-biased technological change associated with ICT throughout much of the developed and developing world. The implications for future developments in inequality both within and between countries are potentially far-reaching.

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1 Introduction

This paper provides the first firm-level econometric evidence on the skill-bias of ICT in developing countries using a unique new data set of almost one thousand manufacturing firms in Brazil and India. While there is a large literature on the effects of skill-biased technological change in developed countries, there is very little evidence on the impact of specific technologies in developing countries, particularly at the micro level. As argued by Berman and Machin (2004), the effects of new technologies on the relative demand for skills are of particular interest in developing countries for three main reasons. First, the social and political implications of increased income inequality may be particularly severe in many developing countries with already high rates of inequality and potentially fragile political institutions. If new technologies are resulting in increased demand for skilled workers, this has important implications for private and public investments in education, as well as for industrial and welfare policies.

Second, the pattern of skill-biased technological change in developing countries helps us to understand the process of international technology diffusion. As discussed below, the results in this paper suggest that new developments in computing technology and associated business practices are now diffusing rapidly through the manufacturing sectors of both Brazil and India, with surprisingly similar implications for the demand for skills in two very different and geographically distant countries. This evidence is consistent with ongoing pervasive skill-biased technological change associated with ICT throughout much of the developed and developing world.

Third, understanding trends in the demand for skill in developing countries may help to throw some light on the surprising persistence of huge disparities in income between the developed and developing world. Berman (2000) points out that factor-biased technological change implies divergent productivity growth across countries with different relative factor endowments. He estimates that an industry or country with twice the capital and skill per less-skilled worker enjoys 1.4%-1.8% faster annual total factor productivity growth due to the effects of factor-bias. This consequence of factor-biased technological change may help to explain why the conditional convergence of per capita income across countries appears to be so slow.

In this paper I use two approaches to investigate the skill-bias of different ICTs in Brazil and India. First I use detailed information on firms' adoption of ICT and the educational composition of their workforce at two points in time to estimate skill-share equations in levels and differences. The results are strongly suggestive of skill-biased ICT adoption, with ICT able to explain up to a third of the average increase in the share of skilled workers in Brazil and up to one half in India. These results are robust to differencing in order to eliminate unobserved firm fixed effects. However, concerns remain over the possible simultaneity of firms' decisions about technology choice and factor mix, so in a second approach I use variation in the relative supply of skilled workers across states within each country to identify the skill-bias of ICT. The results are again consistent with skill-bias in both countries, and are mainly robust to various methods of controlling for unobserved heterogeneity across states. The magnitudes of the estimated effects from both approaches are surprisingly similar for the two countries, consistent with pervasive skill-biased technological change as discussed above.

The structure of the paper is as follows. Section 2 discusses the relevant literature and develops the empirical model. Section 3 describes the new data set and other data used in the estimation. Section 4 then presents the results using firm-level education shares, and Section 5 presents the results using cross-state variation in the supply of skills. A final section concludes.

2 Literature and empirical model

There is a large literature investigating the impact of technological change, and in particular ICTs, on the demand for skills in developed countries.[2] One conclusion from this literature is that skill-biased technological change associated with ICT adoption has played an important role in increasing the relative demand for skilled labour across a number of OECD countries.[3] This consensus is based on a number of observations. First, a number of studies at the industry level have documented within-sector shifts in the composition of employment towards skilled labour at the same time as an increase in its relative price.[4] Second, many of the same studies found that employment shifts towards skill-intensive sectors were too small to be consistent with explanations based on trade with developing countries. Third, several studies have found strong correlations

[2] See Katz and Autor (1999) and Chennells and Van Reenen (1999) for surveys of this literature.
[3] Card and DiNardo (2002) is one of few sceptical contributions to this debate.
[4] Examples include Bound and Johnson (1992), Katz and Murphy (1992) and Berman, Bound and Griliches (1994).

between indicators of technological change and increased demand for skills. For example, Berman, Bound and Griliches (1994) found significant effects of R&D expenditure and computer investment on the growth of the wage-bill share of non-production workers in US manufacturing industries, with computers alone accounting for about one third of the increase.[5]

Further evidence was provided by a second wave of studies which found similar within-industry substitution towards skilled labour in the manufacturing sectors of other OECD economies. Machin and Van Reenen (1998) extended the analysis to six other OECD countries using R&D investment as a proxy for technological change and found similar results. Berman, Bound and Machin (1998) found that shifts away from unskilled labour occurred within similar industries in twelve OECD countries during the 1980s, suggesting 'pervasive' skill-biased technological change. Krugman (1995) pointed out that such pervasive change is more likely to affect relative wages, by reducing the relative price of unskilled labour intensive goods.[6]

More similar to the approach taken in this Paper, another group of studies has found strong evidence for skill-biased technical change associated with computer usage at the establishment and firm level. For example, Doms, Dunne and Troske (1997) used a panel of US plants over 1988-1993 and found strong evidence for skill-bias associated with computer investment.[7] As pointed out by Chennels and Van Reenen (1999) in their survey of the literature, most such studies find robust evidence for skill-bias in the cross section, but not always after controlling for fixed effects. In addition, the literature contains few attempts to find instrumental variables for technology adoption, so estimates may be biased due to simultaneity between firms' choice of technology and factor mix.

More recent studies have examined the mechanisms through which ICT adoption affects the demand for skills. Autor, Levy and Murnane (2003) use detailed data on occupations and find that computers substitute for routine cognitive and manual tasks, and complement non-routine problem-solving and interactive tasks. A number of

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[5] Autor, Katz and Kreuger (1998) extended the analysis over a longer time period and came to similar conclusions.
[6] Leamer (1996) points out that the skill-bias of local technological change has no effect on relative wages if goods prices are fixed.
[7] Similar results were found by Dunne, Haltiwanger and Troske (1997) and Machin (1996).

studies have highlighted the role of complementary organisational innovations that are associated with ICT investment in increasing the demand for skilled labour. For example, Bresnahan, Brynjolfsson and Hitt (2002) find evidence for a panel of US firms that a combination of ICT adoption and new workplace practices are associated with increased training and skill upgrading. Caroli and Van Reenen (2001) find evidence for skill-biased organisational change in panels of French and British establishments.

Recent years have seen a growing amount of evidence for skill-biased technological change in developing countries, though firm-level evidence remains scarce. Berman, Bound and Machin (1998) find some evidence for increasing relative wages of skilled workers in developing countries during the 1980s and hypothesise that this might be related to trade liberalisation.[8] They point out the possibility that skill-biased technological change in the developing world could exacerbate already high levels of income inequality. In extensions to this work, Berman and Machin (2000, 2004) used industry-level data for the 1980s to find evidence for what they term 'skill-biased technology transfer' between high and middle income countries. In particular, the industry pattern of skill upgrading in the US in the 1960s, 1970s and 1980s was highly correlated with the pattern of skill-upgrading in middle income countries in the 1980s, consistent with skill-biased technology transfer. In contrast, they found no consistent evidence of technology transfer from high income to low income countries, although there did appear to have been some within-industry skill upgrading in low income countries other than India.

There is a growing literature on the relationship between rising wage inequality, trade liberalisation and technology adoption in developing countries, particularly in Latin America.[9] However, very few of these studies use specific measures of technology at the firm level, and none use measures of ICT adoption. Hur, Seo and Lee (2005) is a rare example of a study using data on ICT in a developing country. They use industry level data on ICT investment in Korean manufacturing over 1993-1999 and find

[8] A number of other papers had found similar evidence for the effects of trade liberalisation in some developing countries. See for example Hanson and Harrison (1995), Robbins (1995) and Feenstra and Hanson (1996).
[9] Examples include Pavcnik (2002) for Chile, Attanasio, Goldberg and Pavcnik (2004) for Colombia, Verhoogen (2004) for Mexico, and Fuentes and Gilchrist (2005) again for Chile. Gorg and Strobl (2004) use panel data for manufacturing firms in Ghana during the 1990s and find evidence for skill-bias associated with imports of technology-intensive capital goods.

evidence of complementarity with skilled labour after 1996. Similar to the results in this paper, they find evidence that ICT substitutes for low-skilled non-production workers, casting doubt on the usefulness of non-production workers as a measure of skilled labour. Another developing country study using measures of ICT is Sakellariou and Patrinos (2003), who use a survey of graduates in Vietnam and find evidence that computer wage premiums can be explained mainly by unobserved heterogeneity.

There is also very little evidence from Brazil and India specifically, and none that uses data on ICT adoption. Sanchez-Paramo and Schady (2003) study the evolution of relative wages in five Latin American countries using a repeated cross-section of household surveys. They find strong evidence of increases in demand for skilled workers related to trade liberalisation in all countries except Brazil. However, using the same data for Brazil, Pavcnik, Blom, Goldberg and Schady (2003) find that trade reform did contribute to a growing skill premium through induced skill-biased technological change, though the effects on wage inequality were small. While my results are consistent with this finding, I do not use data on trade reforms as these mainly occurred in the early 1990s, long before the period covered by my data.

For India, Berman, Somanathan and Tan (2005) use 3-digit industry level data on the employment and wage-bill shares of non-manual workers and find that skill-biased technological change did arrive in India in the 1990s, following falling demand for skill in the late 1980s. They find that increased output and capital-skill complementarity are the best explanations, with increased output alone predicting almost half of the acceleration in skill-upgrading between the 1980s and 1990s. This raises the possibility that adjustment costs in labour or capital prevented significant skill upgrading in sectors where output was not growing. However, they find that skill upgrading did not occur in the same set of industries in India as it did in other countries, suggesting that it might not be due to international diffusion of recent vintages of skill-biased technologies.

Finally, the results in the second part of this paper are also related to a number of cross-country studies of technology diffusion, most of which have found a positive relationship between ICT adoption and education levels.[10] Most similar to the approach taken in this paper, Doms and Lewis (2006) find that PC adoption rates were higher in

[10] See for example Caselli and Coleman (2001), Pohjola (2003) and Chinn and Fairlie (2006).

US cities with a larger relative supply of college graduates. As discussed below, their results are robust to using instruments for the supply of education. Beaudry, Doms and Lewis (2006) build a simple neoclassical model of the supply of skills, technology adoption and relative wages and fit it to the same data across US cities. They find that cities initially endowed with relatively abundant and cheap skilled labour adopted PCs more rapidly, but relative wages increased most rapidly in those same cities that adopted PCs most intensively. As a result the downwards sloping relationship between relative wages and the supply of skilled labour that existed from 1970 to 1990 had lessened considerably by 2000. However, it is not clear how the effect of technology in this example can be separately identified from lower barriers to the movement of goods, services and labour between cities. The problems involved in identifying the equilibrium relationships between factor supply conditions, technology choice and relative wages are discussed in more detail in Section 2.2 below.

2.1 ICT adoption and the demand for skills

My empirical approach is based on a standard neoclassical model of technology choice. This sub-section first considers the relative demand for high and low skill labour as a function of technology, before discussing some of the econometric issues that arise when attempting to estimate this relationship. The next sub-section then considers the equilibrium relationship between factor endowments, technology choice and relative factor prices across states within a country.

Consider a quasi-fixed translog cost function with three variable factors (high skill labour, low skill labour and materials) and two quasi-fixed factors (physical capital and ICT capital).[11] This seems a natural structure given the difficulties in accurately measuring the cost of physical or ICT capital, especially in a way that varies exogenously across firms. Under the usual assumptions of homogeneity and homotheticity, the wage bill share of high skill workers can be derived as follows:

$$S_H = \alpha_H + \beta_H \ln\left(\frac{w_H}{w_L}\right) + \beta_{HK} \ln\left(\frac{K}{VA}\right) + \beta_{HI} \ln\left(\frac{ICT}{VA}\right) \qquad (1)$$

[11] See Chennels and Van Reenen (1999) for an exposition of this approach. The translog is a relatively flexible functional form, and can be shown to be a second order approximation to an arbitrary functional form. See Christensen, Jorgenson and Lau (1971, 1973).

where w_H and w_L denote the wage of high and low skill workers respectively, K is physical capital, VA is value added, and ICT is ICT capital.[12] If the coefficient $\beta_{HI} > 0$ then this is consistent with ICT being skill-biased.

There are a range of econometric issues that arise in estimating the relationships described above. Consider the basic specification for firm *i* at time *t* as a stochastic form of equation 1:

$$S_{Hit} = \alpha_H + \beta_H \ln\left(\frac{w_{Hit}}{w_{Lit}}\right) + \beta_{HK} \ln\left(\frac{K_{it}}{VA_{it}}\right) + \beta_{HI} \ln\left(\frac{ICT_{it}}{VA_{it}}\right) + f_i + u_{it} \tag{2.2}$$

where f is a fixed effect that is constant over time and u is a stochastic error term that varies over time. Different measured relative wages at the firm level are likely to be contaminated by differences in the quality mix of labour that are imperfectly captured by observable skill or education variables. In order to address this, the relative wage term is replaced in the estimated results by state and industry dummies that control for variation in relative wages across states and industries within the two countries.

The principle problem in estimating equation 2.2 is that both the fixed and the time-varying element of the error term may be correlated with the regressors, leading to biased estimates of the coefficients. For example, some firms may have high quality managers who chose to employ high skill workers and use more ICT, resulting in a positive bias. Or there may be firm-specific shocks that affect both the demand for high skill workers and the choice of ICT.

Unusually, the data set used in this paper contains information on the composition of the workforce for two points in time, allowing estimation of equation 2.2 using a long difference, which eliminates the component of the error term that is fixed over time:

$$\Delta S_{Hi} = \alpha_H + \beta_H \Delta\ln\left(\frac{w_{Hi}}{w_{Li}}\right) + \beta_{HK} \Delta\ln\left(\frac{K_i}{VA_i}\right) + \beta_{HI} \Delta\ln\left(\frac{ICT_i}{VA_i}\right) + \Delta u_i \tag{2.3}$$

The estimate of β_{HI} from this differenced equation is likely to be smaller than that estimated from the levels equation for two main reasons. First, to the extent that firm-specific fixed effects in levels are correlated with ICT adoption, the estimated

[12] This approach has been widely used in the literature relating the demand for skills to technology. See Chennels and Van Reenen (1999) for a discussion.

coefficient in the levels equation will be biased upwards. Differencing removes this source of bias. Second, if there is classical measurement error in (ICT/VA), any attenuation bias will be exacerbated by differencing.[13]

However, the potential also remains that the differenced error term will be correlated with the regressors due to unobservable firm-level shocks. For example, firms may simultaneously increase their ICT adoption and upgrade the skill level of their workforce in response to unanticipated demand or other shocks. As with fixed effects in the levels specification, this is again likely to bias the estimates towards finding evidence of skill-bias associated with ICT adoption.

As discussed in the survey by Chennels and Van Reenen (1999), this issue has generally not been satisfactorily addressed in the literature relating the demand for skills to technology adoption. One approach would be to use exogenous instruments for ICT adoption that are not correlated with other shocks that may affect the demand for skilled workers at the firm level. A potential source of exogenous variation in ICT adoption might be the average change in adoption of ICT by firms in the same industries in countries near the technological frontier such as the US or the UK.[14] If there are exogenous changes in technology at the frontier that affect different industries differentially, then this might be expected to be reflected, possibly after some lag, in patterns of ICT adoption across the same industries in developing countries behind the frontier. For example, Computer Aided Design (CAD) technologies in the garments industry were first developed by firms in developed countries and have now been transferred to some firms in the garments industry in developing countries, often but not always through foreign direct investment or foreign joint ventures.

There are a number of potential concerns with this instrumental variables strategy. First, ICT adoption by firms at the frontier may have direct effects on firms in the same industries behind the frontier through trade and competition effects. Second, common

[13] The simple relationship described above also ignores the possibility of adjustment costs in labour. To the extent that it is costly for a firm to immediately adjust its labour mix optimally in response to its level of ICT adoption, labour adjustment may be lumpy or spread out over time (depending on the exact functional form taken by adjustment costs in labour and ICT capital). Depending on the exact structure of adjustment costs, this could be a third reason why the estimated relationship in differences between ICT adoption and the relative demand for skilled labour could be attenuated towards zero.

[14] This is similar to the approach taken by Berman and Machin (2004) who examine the pattern of skill upgrading across different industries in the US and compare it to other countries.

industry-level shocks might simultaneously determine ICT adoption at the frontier and the relative demand for skills behind the frontier. An obvious example might be the expansion of Chinese firms in the global market for garments following the end of the Multi-Fibre Agreement.

I have investigated using data from the UK and US to create levels and changes of ICT adoption by UK and US firms for the same six industries as in the sample for Brazil and India. However, given that there are only six industries represented in the data, it is not clear whether there is sufficient variation in these instruments to identify the effect of ICT adoption on the demand for skills, and the results suggest that the instruments are too weak for reliable inference. In the absence of other convincing instruments for ICT adoption it is thus not possible to rule out alternative explanations for any correlation between increases in ICT adoption and increases in the relative demand for high skill workers at the firm level.

2.2 ICT adoption as a function of the relative supply of skills

Another potential source of variation that can be used to identify the skill-bias of ICT is differences in the relative supply of skills across regions within countries.[15] Consider the same translog cost function as above, except that ICT capital is now assumed to be variable. From Shephard's Lemma the cost share of ICT is log linear in the factor prices of variable factors as follows:

$$S_{ICT} = \alpha + \beta_H \ln w_H + \beta_L \ln w_L + \beta_M \ln w_M + \beta_{ICT} \ln w_{ICT} + \beta_K \ln\left(\frac{K}{Y}\right) \qquad (2.4)$$

where H refers to high skill workers, L to low skill workers, M to materials, ICT to ICT capital, K to physical capital and Y to output. In the empirical section the baseline assumption will be that the prices of materials and ICT capital do not vary across states within countries. If we also impose the (testable) restriction that the coefficients on high and low skill workers are equal and opposite then the cost share of ICT becomes a function of the log relative price of high to low skill workers:

[15] As discussed in the introduction to this Paper, Doms and Lewis (2006) use a similar approach across US cities. Caroli and Van Reenen (2001) also use a similar approach in the context of examining the skill-bias of organisational changes.

$$S_{ICT} = \alpha' + \beta_H \ln\left(\frac{w_H}{w_L}\right) + \beta_K \ln\left(\frac{K}{Y}\right) \tag{2.5}$$

In this context a negative coefficient β_H is consistent with ICT being skill-biased.

A number of issues arise when attempting to estimate the relationships described in equations 2.4 and 2.5 across states within a country. First, if there is free trade across states then classical Hecksher-Ohlin trade theory predicts that relative factor prices should be equalised. The empirical section shows that there are in fact large differences in the relative wage of high to low skill workers across states within both Brazil and India. A large number of other studies have also found similar persistent violations of relative factor price equalisation across regions within even quite small countries.[16] The interpretation of the estimated coefficient on the log relative wage of high skill workers depends on the source of this identifying variation across states.

There are a number of theoretical reasons why observed relative factor prices may not be equalised across states within a country. One possibility is that *quality-adjusted* relative factor prices are in fact equal, but there is unobserved variation in the quality of high and low skilled workers across states. This source of variation in measured relative wages would tend to bias the estimated coefficient on the log relative wage of high skill workers upwards: if high skill workers in a state are of above average ability, their measured relative wage and levels of ICT adoption in that state are both likely to be higher. Since our hypothesis is that the true value of β_H is negative, this would create a bias towards zero, making it harder to reject the alternative hypothesis that a higher relative price of skilled labour has no effect on ICT adoption decisions.

True deviations from relative factor price equalisation generally require some degree of factor immobility across states.[17] For example, if relative endowments of high skill workers are sufficiently different across states, and workers are not mobile, then in equilibrium there may be multiple cones of Hecksher-Ohlin diversification across different states. In this case, relative factor prices will not be equalised, and the relative

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[16] For example, Bernard et al (2002) find evidence for persistent regional skill price differentials across regions within the UK, even after controlling for unobserved labour quality, while Bernard and Schott (2001) find similar deviations from relative factor price equalisation across US states. Doms and Lewis (2006) find persistent variation in the wage premium of skilled workers across US cities.

[17] See Bernard et al (2002) for a discussion of when relative factor price equalisation may be violated.

wage of high skill workers will remain lower in states with higher relative endowments of high skill workers.[18] Alternatively, non-traded goods or regional variation in goods prices due to transport costs that differ systematically across industries will also result in deviations from relative factor price equalisation.

To the extent that workers *are* mobile across states, we would expect migration to act to reduce variation in both absolute and relative wages, making it harder to identify an empirical relationship between ICT adoption and the relative wages of high skill workers. The extent to which relative wages do in fact vary sufficiently across states in order to identify the relevant relationship then becomes an empirical question.

A second type of econometric concern is the potential endogeneity of relative wages due to unobserved shocks to ICT adoption across states. For example, a shock that increases the average level of ICT adoption in a state may increase the relative wages of more skilled workers, creating a positive bias in the estimated coefficient.[19] As with unobserved variation in worker quality, this is likely to bias the estimated coefficient towards zero, making it harder to reject the alternative hypothesis that a higher relative price of skilled labour has no effect on ICT adoption decisions.

One way to address this issue is to use direct measures of the relative supply of skilled workers across states, either to replace the relative wage term, or as an instrument for relative wages. Consider the former option – estimating directly the reduced form relationship between the relative supply of skilled workers and levels of ICT adoption.[20] If ICT is skill-biased we would expect to find higher levels of ICT adoption in states with a higher relative endowment of skilled workers. A concern in this case is that the relative supply of skills may itself be correlated with other unobserved state characteristics that are themselves associated with higher levels of ICT adoption. For example, states with more educated workers may have better financial markets and thus a lower cost of capital, or states with higher income levels may have more demand for complex products that are more ICT intensive. In part these alternative hypotheses can

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[18] Even though 3-digit industry dummies are included in the regressions, it is possible that there are multiple cones of specialisation even within 3-digit industries. In addition, goods with intermediate factor mixes will continue to be produced in all states in equilibrium, even when there are multiple cones of specialisation.

[19] Of course another consequence could be immigration of skilled workers in response to the demand shock, leading to a reduction in their relative wage, but this possibility seems unlikely.

[20] This is the approach taken by Doms and Lewis (2006) across US cities.

be controlled for using measures of capital intensity or industry dummies, but a better solution in principle would be to use suitable instruments for the relative supply of skills that have no direct effect on ICT adoption. This is the approach taken by Doms and Lewis (2006) who use the historical density of colleges across US cities as an instrument for the share of college educated workers. Another approach is to investigate the relationship in differences in order to eliminate state fixed effects, although this would probably require a relatively long time period due to the slow evolution of the supply of skills over time.

I do not have suitable instruments for the relative supply of skilled workers across states within Brazil and India, while changes in the supply of skills over the time periods available appear to contain insufficient variation to identify the coefficients of interest. In the absence of good instruments for the supply of education it is thus not possible to completely rule out alternative explanations for any positive correlation between the relative supply of skills and ICT adoption across states. My approach to this issue is to include additional firm and state-level controls in order to try and control for unobserved heterogeneity that may affect levels of ICT adoption. This is discussed further in the results section.

If we are willing to maintain the assumption that variation in the relative supply of skilled workers across states is exogenous for ICT adoption (conditional on other included controls), then a second approach to the potential endogeneity of relative wages is to use measures of the relative supply of skills as instruments for the relative wage of high skill workers. In the model discussed above, the relative supply of skills can legitimately be excluded from the ICT cost share equation conditional on the relative price of high skill workers. In other words, relative factor prices are sufficient information for firms to make choices about factor mix. As above, however, we may still be concerned that the relative supply of skills is correlated with other omitted relevant influences.

In order to use the relative supply of high skill workers as an instrument for their log relative wage, the supply of skills must also have sufficient explanatory power in the first stage reduced form. If other factors are fixed, then we clearly expect a negative relationship across states between the relative supply of high skill workers and their log relative wage. However, in equilibrium the relationship between the relative supply of high skill workers and their relative wage will also be affected by the technology and factor mix chosen by firms in response to factor supply conditions. For example, states with initially high relative endowments of skilled workers may adopt ICT more rapidly, which may in turn raise the relative wages of skilled workers.[21]

Acemoglu (2005) investigates the equilibrium bias of technology in a general framework. He shows that as long as the menu of technological possibilities only allows for factor augmenting technologies, an increase in the supply of a factor always induces technological change (or technology adoption) relatively biased towards that factor. In addition, this effect may be strong enough to make the relative marginal product of a factor *increasing* in response to an increase in its supply, thus leading to an upward-sloping relative demand curve. Even if this extreme case is not observed, it remains possible that equilibrium responses to factor endowments may dampen the negative relationship between the relative supply of high skill workers and their relative wage. Ultimately, however, this is an empirical question, and the results section shows that this negative relationship across states appears to be robust in both Brazil and India.

In summary, I take three empirical approaches to investigate the relationship between ICT adoption and the relative supply of high skill workers across states within Brazil and India. First, I estimate the simple OLS relationship across states between ICT adoption and the log relative wage of high skill workers, controlling for a range of other potential influences on ICT adoption. Second, I replace the log relative wage with direct measures of the relative supply of high skill workers across states. And finally, I use measures of the relative supply of high skill workers as instruments for their log relative wage.

3 Data

This section describes the data used for the empirical analysis. It begins by discussing the main features of the data collection process and some contextual information on the two countries, before focussing more closely on the firm-level measures of ICT

[21] Beaudry, Doms and Lewis (2006) find some evidence for this dynamic equilibrium relationship across US cities, although it is not clear to which the same patterns could be equally be explained by falling transport costs or falling barriers to migration across cities.

adoption and educational composition of the workforce. Finally it discusses the data on relative wages and education levels across states within each country.

3.1 Data collection and country context

The data set consists of a unique firm-level survey of nearly one thousand firms in two major developing countries, Brazil and India. The survey was implemented in both countries between April and May 2005 through a series of face-to-face interviews. Interviewers spent up to a day with each firm, with access to senior managers as well as human resources, ICT and finance departments where relevant. This was followed up with phone calls and repeat visits where necessary. The survey was designed to give detailed responses to a set of questions relating to ICT adoption and its timing, changes to the skill and educational structure of employment, and a range of other variables capturing key characteristics of firms' performance and economic environment.

For most questions, data was collected for either two or three points in time over the period 2001-2004. In each country the target sample size was 500 firms across six 3-digit manufacturing industries: auto-components, soaps and detergents, electrical components, machine tools, wearing apparel and plastic products. Stratification was by industry, state and size (employment) with quota sampling. Firms were sampled across nine states in India and thirteen states in Brazil. Table 14 in the Appendix to this paper gives the distribution of the sample over states and industry. In Brazil, a substantial share of the firms were located in Sao Paolo state, which accounted for 35% of total firms surveyed. In India, a similar proportion of firms were in the state of Maharastra (around Mumbai). In terms of response rates, in Brazil the ratio of refusals to responses was 3.4 while in India it was 4.5.[22] The Appendix provides more information about the sampling strategy.

Table 1 provides some basic descriptive statistics for each country on the mean and median values of size (employment), sales, materials and wage shares and capital intensity, as well the mean rate of growth in sales and employment over the period 2001-2003. Median size is very similar across countries, as is the ranking by industry.

[22] These numbers are quite high and raise the possibility of sample selection. Part of the problem in India was incorrect or incomplete contact details. Unfortunately no information was able to be collected on firms that refused. Interviewers did not report any systematic differences between firms that refused and those that responded.

Mean employment growth is quite similar in both countries, although median growth in India is double that in Brazil.

The materials shares were very similar across countries, but in India the mean and median wage shares were only 30-40% of those in Brazil. Capital intensity was also higher in Brazil but by a far smaller margin. Exact data on employment, sales, materials and capital is not available for all firms, particularly materials and capital in Brazil.[23]

There were significant differences between the two countries in the broader economic environment over this period. In India, GDP growth exceeded 6% over the period, while in Brazil average growth was around 2%. While this reduced the income gap between the two countries, by 2004 Indian per capita income was only around 13% of Brazil's, with notably lower literacy, schooling enrolment and other social indicators as well. A far higher proportion of India's population lives in rural areas – 72% compared to only 16% in Brazil.[24] Both countries significantly reduced tariff rates on manufactured goods during the 1990s, and tariff rates on imports of ICT hardware were extremely low in both India and Brazil before and during the sample period. In terms of inequality, according to the UN Development Programme's 2006 Report, the Gini coefficient in Brazil was 0.58 in Brazil in 2003, while it was only 0.33 in India in the most recent data for 2000.

In terms of available country-level ICT indicators, Table 16 in the Appendix shows major disparities in almost all indicators whether relating to access, quality, efficiency or expenditure. ICT expenditure as a share of GDP was 6.7% in 2004 in Brazil as against 3.7% in India. Access to communications was vastly lower in India than in Brazil, whether for fixed line, mobile or Internet and broadband coverage. This is largely explained by the fact that a far larger proportion of India's population still lives in rural areas; differences are likely to be less significant in urban areas, although comparable data on this is not available. In terms of ownership and market structure, in Brazil private ownership of telecoms runs alongside competition in provision. In India, by 2004 ownership remain mixed with limited competition, except for internet service

[23] Brazilian managers often said they were not willing to provide this information as they considered it strategic. It is also possible they were sensitive about disclosure of information to the authorities.
[24] UN World Urbanisation Prospects 2005

providers.[25] Quite clearly, by these indicators, Brazil remains ahead of India in terms of overall ICT adoption and investment.

3.2 Firm-level data on ICT adoption

In order to summarise the intensity of a firm's adoption of ICT, the data contains an overall adoption index constructed from five possible responses to a question regarding the degree of ICT use in 2001 and 2003. These ranged from IT not being used at all, to all processes being automated and integrated into a central system.[26] Figure 1 plots the distribution of responses for both years using the 1-5 scale that was applied (the thin bars are for 2001 and the thicker ones are for 2003).

Several characteristics of these distributions stand out. First, the share of Indian firms with little or no adoption (scores of 1 or 2, corresponding to no ICT at all or simply desktop PC applications) is higher than in Brazil in both years. In 2001 over 60% of Indian firms were using ICT in a minimal way, as against 45% in Brazil. Second, there has been a rapid increase in the share of firms using ICT in both countries. The share of firms with minimal use had declined substantially by 2003 while the gap between Brazil and India had remained roughly constant. Third, it is still the case that by 2003 a far smaller share of Indian firms had the highest adoption scores (4 or 5) than in Brazil. At the top end of the distribution (5) nearly 30% of Brazilian firms had automated almost all processes with ICT integrated into a central system, as against only 10% of the Indian sample.

Interestingly, the distribution across responses for India in 2003 is extremely similar to that for Brazil in 2001, suggesting that Indian firms in these six industries lag their Brazilian counterparts by about 2 years on average in the intensity of their ICT adoption. This is a much smaller gap than implied by the country-level statistics discussed above, probably in part due to the much higher proportion of the Indian population still living in rural areas and dependent on agriculture.

Tables 2 and 3 provide some further descriptive statistics for a set of indicators of ICT adoption for both the level in 2003 and the change over 2001-2003. The first two measures relate to workforce usage of ICT: the percentage of non-production workers

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[25] World Bank (2006)
[26] The precise definition is given in the Appendix.

using PCs (on a daily basis as part of their work), and the percentage of production workers using ICT-controlled machinery. The difference between the countries in levels is fairly similar for both measures, with the mean and median in India between two-thirds and three-quarters of the Brazilian level. Average changes over time for these variables are fairly similar in the two countries. A similar picture emerges for the adoption index described above, as well as for an alternative ICT usage index. This takes integer values from 4 to 16, and is constructed from a question regarding the intensity of usage of ICT for four business functions: accounting services, inventory management, marketing and product design, and the production process.[27]

All four of these measures are used in the empirical analysis in order to capture different aspects of a firm's ICT intensity. The two workforce usage measures are likely to be less affected by measurement error, and are also likely to relate most closely to the skill requirements of the non-production and production workforce. The two ICT indices are constructed from subjective answers to qualitative questions and so may be more subject to measurement error. However, they may also capture broader aspects of a firm's ICT adoption and the way that ICT is integrated into business processes.

3.3 Occupation and education shares

The data set also contains detailed information on the composition of the workforce by occupation group and education level for two points in time, 2001 and 2004. Table 4 shows the mean occupation shares in 2004 for the two main occupation groups – 'production workers' (which includes supervisors but not managers) and 'admin and clerical workers'.[28] Within each of these two occupation groups we also observe a breakdown by education level into five groups based on the highest completed level of education – 'less than primary', 'primary but not lower secondary', 'lower secondary but not upper secondary', 'upper secondary but not college', and 'college'.

From the table it is clear that production workers make up the biggest share of workers in both countries, on average almost 70% in Brazil and 62% in India. Within the production workforce the educational composition is fairly similar for both countries, although the Indian workers appear to be more concentrated in the college group.

[27] Details of variable construction are in the Appendix.
[28] The other groups were 'managers' and 'other.'

Admin and clerical workers are significantly more educated than production workers in both countries, with an extremely small proportion having less than lower secondary education. Admin and clerical workers are significantly more likely to have a college education in India than Brazil.

At first sight the fact that a much higher proportion of admin and clerical workers in India have a college education appears surprising. However, this is consistent with anecdotal evidence of fierce competition in India for formal sector jobs within a constrained manufacturing sector, with many college graduates performing jobs that do not require a college education. This is also consistent with the fact that the average relative wage of non-production to production workers in the sample is about 8% lower in India than in Brazil, despite the fact that non-production workers in India are significantly more educated on average relative to production workers.

Table 5 shows the average changes in education shares within the two groups, (production workers and admin and clerical workers) between 2001 and 2004. The composition of both types of workers became more educated over the period in both countries, with a shift within production workers away from those without lower secondary education and towards those with upper secondary and college education. This shift was more pronounced in Brazil than in India, with the share of workers with upper secondary or college education growing by 3.7 percentage points in Brazil but only 1.8 percentage points in India. Within admin and clerical workers, the shift was more similar across the two countries, with increases in the share of college educated workers at the expense of those without college.

The final sample is limited to firms with complete data on all four ICT measures presented in the previous section, on all education shares in both 2001 and 2004, and to those firms for which the shares for each type of worker sum to 100% in both years. After cleaning, the sample for production workers contains 335 observations in Brazil and 446 observations in India, while for admin and clerical workers the sample size is 353 in Brazil and 449 in India.

3.4 Relative wages and education at the state level

In order to investigate the relationship between ICT adoption and the supply of skills across states, I also use data on relative wages of more skilled workers and education across states within the two countries. This data is presented in Table 22 in the Appendix. The first column contains a measure of the log state mean relative wage of non-production workers (admin and clerical plus managers) compared to production workers in 2003. This is constructed from the firm-level data in the sample and averaged to the state level. There is considerable variation across states in both countries, and, as discussed above, the average log relative wage of non-production workers is slightly higher in Brazil than in India. For Brazil, column (2) presents an alternative measure using household survey data for 2003 – the log state mean relative wage of workers with upper secondary education or above to those without (this corresponds to 11 or more years of education). The mean is very similar to the measure in column (1), and the two are positively correlated across states, with a correlation coefficient of 0.45 that is significant at the 1% level.

Column (3) shows the literacy rate across Indian states, while Column (4) shows a roughly equivalent measure of basic education across Brazilian states: the proportion of the population with at least one year of formal education. Column (5) shows the proportion of the population with college education for both countries. Within India, Delhi is an obvious outlier, consistent with its role as India's administrative and political capital. This issue is discussed in more detail below in Section 5.3. Within Brazil, the two main cities, Sao Paulo and Rio de Janeiro, also appear to be outliers, though to a lesser extent.

4 ICT adoption and education shares

This section investigates the relationship between ICT adoption and the demand for skills at the firm level. Following the discussion in Section 2, the basic specification in levels is as follows, estimated separately for production workers and admin and clerical workers:

$$S_{nijs} = \beta_n ICT_{ijs} + \alpha' x_{ijs} + IND_j + STATE_s + f_i + u_{nijs} \tag{6}$$

where S is the 2004 employment share of education group n in firm i, industry j and state s, ICT is a measure of ICT intensity in 2003, x is a vector of firm controls that includes size, age, foreign ownership and joint ventures, listed status, state ownership and union membership, and *IND* and *STATE* are a full set of industry and state dummies.[29] The error term is assumed to be composed of an unobserved firm fixed effect *f* that is likely to be correlated with ICT adoption, and a stochastic error *u* that may or may not be correlated with the regressors. A positive estimate of β_n is consistent with ICT adoption being complementary with the labour of education group *n*. In the tables that follow, only the estimate of β_n is shown for each education group and for each measure of ICT adoption.

This paper follows several previous studies by using employment shares rather than wage bill shares as the dependent variable. Although theoretically less appropriate within this simple framework, there are a number of reasons for examining factor quantities separately from factor prices. For example, other models may suggest different reasons why technology may be correlated with cost shares. The simple model described in Section 2 assumes that factor prices are exogenous, but if wages are set by some form of bargaining, then workers may be able to capture some of the rents from innovation.[30] If high skill workers are more able to capture rents than low skill workers then the correlation between technology and cost shares could be driven purely by changes in relative wages for this reason. Another advantage of using employment rather than wage shares is that it allows workers to be grouped by education level rather than occupation – firms do not keep information on average wages by education levels.

As discussed in Section 2, unobserved firm fixed effects are likely to bias the levels results in favour of finding evidence for skill-bias. Unusually the data contains observations on education shares and ICT at two points in time, allowing a long difference specification to be estimated as follows:

$$\Delta S_{nijs} = \beta_n \Delta ICT_{ijs} + \alpha' x_{ijs} + IND_j + STATE_s + e_{nijs} \qquad (7)$$

where the difference in *S* is over the period 2001-2004 and the difference in *ICT* is over the period 2001-2003. In what follows I compare the estimated coefficients from equation 6 to those from equation 7. As discussed in Section 2 there are two main reasons why we might expect smaller estimated coefficients in the difference

[29] As discussed above, capital stock is not available for all firms, particularly in Brazil. Results controlling for potential capital-skill complementarity are presented in the robustness section later on.
[30] For example, Van Reenen (1996) finds evidence for rent capture from innovation for UK firms.

specification: fixed effects and measurement error. However, there remains the possibility that simultaneity will still bias the results towards evidence of skill-bias.

4.1 Results in levels

Before discussing the econometric results, Figure 2 presents a graphical illustration of the bivariate relationship for each country between the percentage of production workers using ICT controlled machinery and the percentage with upper secondary education or above. For each quartile of the percentage using ICT controlled machinery, the bars show the mean value of the percentage with upper secondary education or above. The relationship is clearly increasing and monotonic across quartiles for both countries, with the average percentage of production workers with upper secondary education or above roughly doubling between the bottom ICT-using quartile and the top quartile in Brazil, and increasing by over 50% in India.

Table 6 shows the results of estimating equation 6 for production workers. Each row corresponds to a different set of regressions using a different measure of ICT adoption, and the estimated coefficient and robust standard error are shown for each education group. For each country the average share for each education group is shown along the top row. All specifications also include dummies for firm size, state, industry and age, as well as controls for foreign ownership and joint ventures, state ownership, listed status and union membership.

The results for Brazil are strongly suggestive of skill-bias associated with ICT using all four measures of ICT intensity, with negative coefficients on the shares of the two lowest education groups and positive coefficients on the upper secondary and college groups. The results for India are similar though slightly weaker, particularly for the two ICT indices.

Conceptually, the most relevant measure of ICT for production workers is the percentage of production workers using ICT controlled machinery. Using this measure the results are strikingly similar across the two countries. Consider the impact of a one percentage point increase in the percentage of production workers using ICT controlled machinery on the proportion of production workers with upper secondary education or above, by summing the coefficients on the top two education groups. In both countries this corresponds to an increase of just over 0.3 percentage points in the share of production workers with upper secondary education or above, with the increase concentrated in Brazil on those with upper secondary but not college, and in India on those with college or above. Alternatively, consider a one standard deviation increase in the percentage of production workers using ICT controlled machinery, which is an increase of 31 percentage points in Brazil and 23 percentage points in India. This is associated with a 9.8 percentage point increase in the share of production workers with upper secondary or above in Brazil and a 7.5 percentage point increase in India, corresponding to between a quarter and a third of a standard deviation in each case.

Table 7 shows the equivalent levels results for admin and clerical workers. For Brazil the results are again strongly suggestive of skill-bias. As might be expected for admin and clerical workers, the strongest results are in the first row using the percentage of non-production workers using PCs, while there is no evidence of skill-bias using the percentage of production workers using ICT controlled machinery. However, in contrast to the results in Table 6 for production workers, there is no evidence in Table 7 for skill-bias associated with ICT for admin and clerical workers in India. One possible explanation for this is that, as discussed above, the average college share for admin and clerical workers is much higher in India, at 76.6% compared to only 34.6% in Brazil. It is possible that there is a relationship between ICT and the distribution of higher level skills *within* the college share in India, but there is no way of picking this up using the available data.

4.2 Results using long differences

Overall the results in levels are consistent with skill-bias associated with ICT adoption. However, as discussed above, this conclusion may be driven by unobserved firm fixed effects that are correlated with ICT. This sub-section considers the equivalent results in long differences in order to eliminate any fixed effects.[31]

Before considering the econometric results, Figure 3 presents the same bivariate graphical result as Figure 2 except in long differences.[32] While the mean change in the percentage of production workers using ICT controlled machinery does increase on

[31] As discussed above, however, there remain concerns over the potential endogeneity of changes in ICT adoption due to simultaneity or correlated shocks to ICT adoption and the demand for skills. If anything, this is again likely to bias the results in favour of finding evidence for skill-bias.
[32] The first "quartile" in each country now contains more than 25% of the sample due to zeros.

average across quartiles, it is no longer monotonic in either country. The proportional increase in the change between the bottom and the top quartile is larger than in the levels case, but the absolute percentage point increase is significantly smaller.

Table 8 shows the results of estimating equation 7 for production workers. As before, each row corresponds to a different measure of ICT adoption, and the estimated coefficient and standard error is shown for each education group. For each country the average percentage point change in each education share is shown along the top row. All specifications also include dummies for firm size, state, industry and age, as well as controls for foreign ownership and joint ventures, state ownership, listed status and union membership.

Overall the results are consistent with skill-bias, but as expected they are significantly weaker than the levels results in Table 6. With the two workforce usage measures there is only very weak evidence for skill-bias in Brazil. The overall pattern is similar to the levels results, but the size of the coefficients is on average less than one third of the equivalent levels estimates in Table 6. For India there is fairly strong evidence for skill-bias using the most relevant ICT measure – the percentage of production workers using ICT controlled machinery – but again the overall size of the effect is about one quarter of the levels case. For both countries the results are strongest using the ICT usage index, but again the size of the coefficients is on average between one quarter and one third of the equivalents in Table 6.

Using these coefficients we can ask what proportion of the average increase in the employment shares of production workers with upper secondary or college education can be associated with increases in ICT usage. In Brazil the average increase in the ICT usage index is 1.35 and in India it is 1.69. Combining these numbers with the coefficients in columns (4) and (5) of Table 8 suggests that increased ICT usage can explain about 32% of the average increase in the share of production workers with upper secondary education or above in Brazil (1.2 percentage points out of an average increase of 3.7 percentage points), and about 47% of the average increase in India (0.9 percentage points out of an average increase of 1.8 percentage points). To the extent that the estimated coefficients are attenuated by the presence of adjustment costs or measurement error, these numbers are underestimates of the explanatory power of increased ICT usage, but if the estimated coefficients are biased in favour of finding evidence of skill-bias due to simultaneity between ICT usage and skill upgrading, then they may overstate the role played by ICT.

Table 9 shows the equivalent difference results for admin and clerical workers. In Brazil there is no strong evidence of skill-bias with the two workforce usage measures of ICT. However, there is strong evidence that ICT is biased towards workers with college education using the ICT usage index. In this case, the size of the effect is only slightly smaller than in the levels estimates in Table 7. In India there is evidence of skill-bias away from workers without upper secondary education with all four ICT measures. This is in contrast to the levels results in Table 7 where there was no evidence of skill-bias in India.

Again we can ask what proportion of the increase in the percentage of admin and clerical workers with college education can be associated with increases in ICT usage. The numbers are fairly similar to those for production workers, though slightly smaller in the case in India. In Brazil increased ICT usage can explain about 40% of the average increase in the share of admin and clerical workers with college education or above (1.2 percentage points out of an average increase of 3.0 percentage points), while in India the equivalent number is 17% (0.5 percentage points out of an average increase of 3.0 percentage points). As before these numbers may over or understate the role of increased ICT usage to the extent that the estimates are affected by measurement error, adjustment costs or simultaneity bias.

To summarise, there is evidence of skill-bias associated with ICT adoption in both levels and differences, though the results are generally weaker in differences. For production workers ICT usage appears to be complementary with upper secondary and college education, while for admin and clerical workers ICT is associated with a bias towards college education away from workers without college. In general the size of the estimated effects is strikingly similar across the two countries, though possibly slightly smaller on average in India than in Brazil.

4.3 Controlling for capital intensity

The results above do not control for changes in physical capital intensity. As discussed above, data on capital stock is not available for all firms, particularly for Brazil. As a robustness check, this sub-section presents results both with and without controlling for capital intensity for those observations where capital is available. The basic specification to be estimated in levels is now as follows:

$$S_{nijs} = \beta_{nI} ICT_{ijs} + \beta_{nK} \ln K_{ijs} + \beta_{nY} \ln Y_{ijs} + \alpha' x_{ijs} + IND_j + STATE_s + f_i + u_{nijs} \qquad (8)$$

where all notation is as above, K is a measure of conventional capital stock and Y is value added. To be as flexible as possible, capital and value added are included separately, instead of imposing the homotheticity restriction that $\beta_{nK} = -\beta_{nY}$. The equivalent specification in differences is as follows:

$$\Delta S_{nijs} = \beta_{nI} \Delta ICT_{ijs} + \beta_{nK} \Delta \ln K_{ijs} + \beta_{nY} \Delta \ln Y_{ijs} + \alpha' x_{ijs} + IND_j + STATE_s + e_{nijs} \qquad (9)$$

The levels results for production workers and admin and clerical workers are presented in Tables 17 and 18 in the Appendix, using as ICT measures the percentage of production workers using ICT controlled machinery and the percentage of non-production workers using PCs respectively. In each case the results are first presented without controlling for capital and value added, and then on the same sample but including the extra controls. Consider first the results for production workers in Table 17. The results are as before consistent with skill-bias, but most importantly the estimated coefficients on the percentage of production workers using ICT controlled machinery are extremely similar whether the additional controls for capital intensity are included or not. Turning to the coefficients on log capital and value added, in Brazil the coefficients on capital and value added are generally of opposite sign as expected, and there is some evidence of capital-skill complementarity for upper secondary and college educated workers.[33] In India the pattern is less clear.

For admin and clerical workers in Table 18 there is less evidence of skill-bias, but as with production workers the estimates are not significantly different from those in the full sample in Table 7. However, as with production workers the most important result is that the coefficients on the percentage of non-production workers using PCs are not significantly affected by including the controls for capital intensity. There is little evidence for capital-skill complementarity for admin and clerical workers in either country.

[33] The hypothesis that the coefficients on capital and value added are equal and opposite is never rejected, even at the 10% level.

Tables 19 and 20 present the equivalent results for the difference specification, this time using the ICT usage index for both types of workers, since this is the measure for which the results are strongest in the full sample. The overall conclusion is the same as for the levels results: there remains evidence for skill-bias of ICT, and the estimated coefficients on ICT usage are not significantly affected by including controls for capital intensity. There is no strong evidence for capital skill complementarity for either type of worker in differences. Overall these results suggest that the conclusions from the previous section are not significantly altered by controlling for conventional capital intensity.

5 Regional variation in the supply of skills

As discussed in Section 2, another potential source of variation that can be used to identify the skill-bias of ICT is differences in the relative supply of skills across states within countries. This is the approach taken in this section. Following the discussion in Section 2 the basic specification is a stochastic version of equation 5 as follows:

$$ICT_{ijs} = \beta \ln\left(\frac{w_H}{w_L}\right)_s + \alpha' x_{ijs} + IND_j + u_{ijs} \qquad (10)$$

where *ICT* is a measure of ICT intensity in 2003 for firm *i* in industry *j* and state *s*, (w_H / w_L) is the state mean relative wage of high to low skilled workers (defined in various ways below), *x* is a vector of firm controls that includes size, age, foreign ownership and joint ventures, listed status, state ownership and union membership, and *IND* represents a full set of 3-digit industry dummies. As discussed in Section 2, including the log relative wage instead of the log wage of high and low skill workers separately involves imposing a linear restriction on the general expression in equation 4. However, this restriction is never statistically rejected in either country at even the 10% significance level. Finally, since relative wages are measured at the state level, standard errors are adjusted for clustering by state.

As with the results in the previous section I do not include controls for conventional capital intensity in the main results due to data limitations. If we assume that capital is a variable factor in equilibrium then the controls for firm size, age, ownership and industry should capture much of the variation in the cost of capital across firms. However, we might be concerned that there remains variation in the cost of capital across states that is correlated with the relative wage of high skill workers. For this reason I present robustness results in Section 5.4 below on a sub-sample of observations for which capital intensity is available. The same concerns may arise over unobserved heterogeneity across states in the cost of other factors such as materials, energy or even ICT capital itself. As discussed in Section 2, I cannot control for all unobserved heterogeneity across states, but in Section 5.4 I experiment with various additional controls, including materials intensity, state level income per capita, and measures of the frequency of power-related problems across Indian states.

5.1 ICT adoption, relative wages and education across states

Before presenting the econometric results, Figures 4 to 7 provide graphical illustrations of the identification strategy. Figure 4 plots for Brazil the state mean percentage of non-production workers using PCs against the log state mean relative wage of workers with 11 or more years of education (corresponding to upper secondary education or above). The size of the circle for each of the 13 states is proportional to the number of observations from that state in the sample, and the fitted lines represents a weighted linear fit.

The first thing to note is the wide variation across states in the relative wage of more educated workers, with about a 50% difference between the highest and lowest states. Interestingly, the spread from the left, with the states with the lowest relative wage of more educated workers, to the right is very similar to a northward geographical journey up the Atlantic coast of Brazil, with the Southern states of Santa Catarina and Parana having the lowest relative wage, followed by Sao Paulo, Goias, Minas Gerais, Rio de Janeiro and Espirito Santo in the middle, and finally the three north-eastern states of Bahia, Pernambuco and Ceara on the right hand side. The only exceptions are the southernmost state of Rio Grande do Sul and the northernmost Amazonian state of Para. Thus, with only two exceptions the states with the lowest relative wage are geographically furthest from those with the highest relative wage. One interpretation is that persistent violations of relative factor price equalisation in Brazil are supported by transport costs and/or goods that are not traded over long distances.

The second interesting aspect of Figure 4 is the strong negative relationship between PC usage and the relative wage of more educated workers. The slope of the linear fit is significant at the 1% level, and the R-squared is over 50%. As discussed in Section 2, this is consistent with ICT adoption being biased towards more educated workers. Any unobserved variation in worker quality across states that explained the variation in relative wages would tend to produce a less negative relationship, since if more educated workers are on average of higher quality in the North East, we would expect higher levels of ICT adoption in those states. Equally, to the extent that high levels of ICT adoption in some of the southern states is driven by unobserved shocks this would also tend to produce a less negative relationship by increasing the relative wage of more educated workers.

Figure 5 replaces the log relative wage with a measure of the proportion of the population in 2001 with college education (equivalent to 15 or 16 years of education). Although the fit is slightly less good than in the case of relative wages, the positive relationship is highly significant at the 1% level. Interestingly, the two largest cities, Sao Paulo and Rio de Janeiro, appear to be outliers. It is possible that this is driven by the large financial and service sectors in these cities, which attracts a large number of college educated workers.

If we assume that the supply of educated workers is exogenous for ICT adoption, this provides strong evidence that ICT is skill-biased towards college educated workers in Brazil. However, as discussed in Section 2, we may be concerned that states with high proportions of college educated people also have other characteristics that are favourable to ICT adoption. Without good instruments for the supply of education, it is not possible to completely rule out alternative explanations of this sort.

Figures 6 and 7 present the same relationships across Indian states in the sample.[34] While the fit in Figure 6 is slightly less good than the equivalent in Figure 4 for Brazil, the negative relationship between PC usage and the relative wage is again highly significant, with an R-squared of 35%. Figure 7 again replaces the relative wage with the proportion of the population with a college degree.[35] The relationship is again positive and highly significant, although this is partly driven by 169 observations in the

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[34] Figure 6 uses a measure of the relative wage in 2003 of non-production to production workers, averaged up to the state level using in-sample data. The average value and standard deviation across states are similar to the measure of the relative wage of workers with 11 or more years of education used in Brazil, as shown in table 22.

[35] Delhi is excluded from Figure 7 as it is an outlier with 22.3% of the population having a college degree. As discussed later on this is likely to be driven by Delhi's position as the administrative and political capital of India.

state of Maharastra (which contains Mumbai).[36] It is striking that Maharastra, as India's financial and service sector hub, is an outlier in a similar position to Sao Paulo and Rio de Janeiro in Brazil. Without the influence of these states, with their high levels of college education, the fitted lines in Figure 5 and Figure 7 would both be considerably steeper.

5.2 Variation across Brazilian states

Table 10 presents the econometric results for Brazil, with each column using a different measure of ICT adoption as the dependent variable. As discussed above, all specifications also include dummies for firm size, industry and age, as well as controls for foreign ownership and joint ventures, state ownership, listed status and union membership. All standard errors are adjusted for clustering at the state level.

Consider first the results in column (1) using the percentage of non-production workers using PCs as the dependent variable. Row A uses the log of the in-sample state mean of the relative wage of production and non-production workers in 2003 as a measure of the supply of skills. Consistent with skill-bias the coefficient is negative but it is not significant. Five of the thirteen Brazilian states in the sample contain less than 10 observations, potentially making the in-sample state mean of relative wages a noisy measure of the relative supply of skills. For this reason in Row B external data from household surveys is used to construct the log of the state mean relative wage of workers with upper secondary education or above compared to those without.[37] The coefficient becomes more negative and strongly significant, suggesting that firms in states where the relative wage of more educated workers is higher have lower proportions of admin and clerical workers using PCs. This is consistent with the graphical illustration in Figure 4.

Row C uses the proportion of the population with college education in each state as an alternative measure of the supply of skilled workers. Consistent with the graphical

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[36] Berman, Somanathan and Tan (2005) find that skill-biased technological change was fairly widespread across Indian states during the 1990s, though West Bengal was a notable exception. In general there is very little relationship between measured ICT usage in my sample and their measures of increases in the demand for skill across states, though of course the time periods are different.

[37] As discussed in Section 3, this is positively correlated across states with the in-sample measure of the log relative wage of non-production workers, with a correlation coefficient of 0.45 that is significant at the 1% level.

illustration in Figure 5 the coefficient is positive and highly significant, suggesting that an extra 1 percentage point of the population having a college education is associated with a 5.6 percentage point increase in the proportion of admin and clerical workers using PCs. In Row D the proportion of the population with at least one year of formal schooling is added as an additional regressor, in order to investigate whether it is indeed college education that is most important for PC adoption or whether a more broad-based measure of education has more explanatory power. Interestingly the latter is the case, though it is not possible to draw too strong a conclusion from this, since the two variables are fairly highly correlated across states, and it is possible that measurement error is higher as a proportion of the average value for college education.

As discussed in Section 2, Row E uses the proportion of the population with a college education as an instrument for the relative wage of more educated workers. The results of the first stage regression are contained in column (1) of Table 21 in the Appendix, which shows that the college share enters negatively and significantly as expected. However the explanatory power of the instrument is not very large, with a partial R-squared of 11%, and the F-statistic is only 3.41, suggesting the possibility of weak instruments according to the critical values presented by Stock and Yogo (2004). Consistent with this the IV coefficient in Row E of Table 10 appears to be only weakly identified, although it is significant at the 10% level. However, the IV estimate is more negative than the equivalent OLS estimate in Row B as expected, suggesting that unobserved worker quality or shocks to ICT adoption across states may be biasing the OLS estimate upwards. However, a Hausman test does not reject the hypothesis that the coefficients are the same, even at the 10% level.

To address the low power of the instrument, Row F includes the proportion of the population with at least one year of formal education as an additional instrument. The first stage in column (2) of Table 21 suggests that this instrument is strongly negatively associated with the relative wage of more educated workers.[38] The explanatory power of the instruments is increased dramatically, with a partial R-squared of almost 70% and

[38] Conditional on this additional instrument the proportion of the population with a college degree becomes significantly positive, but it is difficult to read very much into this result. One possibility is that, as discussed in Section 2, the relative demand curve for college educated workers may be upwards sloping in equilibrium, due to the effect of increased ICT adoption on the marginal product of college educated workers.

an F-statistic of 17.80. Correspondingly the IV estimate in Row F of Table 10 becomes more accurately estimated and much closer to the OLS estimate in Row B. In addition the Hansen test does not reject the over-identifying exclusion restriction, with a p-value of 0.186.

Thus the original OLS estimate in Row B appears to be robust to instrumenting the relative wage of more educated workers with measures of the relative supply of skills, suggesting that any OLS bias is quite small. As discussed in Section 2, however, there remains a concern that the supply of skills may be correlated with other unobserved factors across states that influence ICT adoption. I return to this later on in the robustness section.

These results for PC usage are not replicated in Brazil using the other ICT measures in columns (2) to (4) of Table 10. One possible explanation is that measurement error in ICT is lower using PC usage since PCs are relatively simple to identify and count. Doms and Lewis (2006) use PC usage to measure ICT adoption across US cities for a similar reason.

5.3 Variation across Indian states

Table 11 shows equivalent results for India. Again, consider first the results using PC usage in column (1), which are qualitatively extremely similar to those for Brazil. As in the Brazilian case, Row A uses the log of the in-sample state mean of the relative wage of production and non-production workers in 2003 as a measure of the supply of skills.[39] The coefficient is about twice as negative as the equivalent coefficient in Brazil, and highly significant. As before this is consistent with the graphical illustration in Figure 6, which showed a strong negative correlation between the relative wage of non-production workers and the percentage of non-production workers using PCs.

As discussed in Section 3 and shown in Table 22, Delhi stands out as an obvious outlier in the data on education levels across Indian states. For example, the proportion of the 15-59 year old age group with a college degree in 1999-2000 is 22.3% in Delhi, but the next highest state is Maharastra with 6.8%, and the lowest is Andhra Pradesh with

[39] In India all but one state in the sample has more than 10 observations, making the in-state state average relative wage of non-production workers a less noisy measure of the relative supply of skills than in Brazil.

5.2%. This is consistent with Delhi's position as the administrative and political capital of India, but is unlikely to be proportionately reflected in rates of ICT adoption by manufacturing firms. In addition, the proportion of people with a degree is surprisingly marginally *positively* correlated across states with the log mean relative wage of non-production workers in the full sample (with a correlation coefficient of 0.12), but highly significantly *negatively* correlated as expected once Delhi is dropped, with a correlation coefficient of –0.75 that is significant at the 1% level.

For this reason Delhi is dropped from the specifications using education data in Rows C to F of Table 11. Before discussing these results, Row B shows for comparison the same specifications as in Row A, except that observations from Delhi are dropped from the sample. Reassuringly the results are very similar.

As with the Brazilian case, Row C uses the proportion of the population with college education in each state as an alternative measure of the supply of skilled workers. Again consistent with the graphical illustration in Figure 7, the coefficient is positive and highly significant, and is about three times larger than the equivalent coefficient in Brazil. The size of the coefficient suggests that an extra 1 percentage point of the population having a college education is associated with about a 17 percentage point increase in the proportion of admin and clerical workers using PCs. One possible explanation for this larger coefficient in India is the much higher proportion of the population living in rural areas and dependent on agriculture. If most rural dwellers are largely separated from urban labour markets, then a 1 percentage point increase in the proportion of the total (urban and rural) population with a college education corresponds to a much larger increase in the proportion of the urban population with a college education, assuming that the vast majority of people with a college education live in urban areas.

In Row D the literacy rate is added as an additional regressor, in order to investigate whether it is indeed college education that is most important for PC adoption or whether a more broad-based measure of education has more explanatory power. Unlike the Brazilian case, college education remains positive and highly significant, while the more broad-based literacy measure is insignificant in this case.

As with the Brazilian case, Row E uses the proportion of the population with a college education as an instrument for the relative wage of non-production workers. The results of the first stage regression are contained in column (1) of Table 21, which shows that the college share enters negatively and highly significantly as expected. The explanatory power of the instrument is higher than in the Brazilian case, with a partial R-squared of 56% and an F-statistic of 16.84. The IV coefficient in Row E of Table 11 is negative and highly significant. As with the Brazilian case the direction of any OLS bias appears to be positive (compare Row E to Row B), consistent with expectations, but again a Hausman test does not reject the hypothesis that the OLS and IV coefficients are the same, even at the 10% level.

For symmetry with the Brazilian results, Row F includes the literacy rate as an additional instrument. The additional power of the instrument is not very large and the results are very similar to those in Row E. A Hansen test of the over-identifying restriction does not reject.

Whereas in the Brazilian case this overall pattern of results was only observed for PC usage in column (1), in India the pattern is repeated for the ICT adoption index in column (3), and to a lesser extent the ICT usage index in column (4). The exception is when the proportion of production workers using ICT controlled machinery is used as the dependent variable in column (2). In this case the coefficients on the relative wage of non-production workers in Rows A and B are negative but not significant. Given that the dependent variable is a measure of technology usage by *production* workers it is not very surprising to find no significant result in this case. More interesting are the results using direct measures of the supply of educated workers in Rows C and D. In Row C the coefficient on the percentage with a college education is small and insignificant. In Row D the coefficient on the college share becomes negative but insignificant, and the coefficient on the literacy rate is positive and highly significant. This is the only ICT measure for which this pattern of results is observed, possibly suggesting that ICT usage by production workers is more complementary with basic skills (as captured by the literacy rate), while ICT usage by non-production workers is more complementary with higher-level skills associated with college education.[40]

[40] A note of caution in this interpretation is the fact that in the firm-level results in Section 4, ICT usage by production workers was found to be positively associated with both levels and changes in the proportion of production workers with college education (see Tables 6 and 8).

5.4 Controlling for capital and other factors

As discussed above, we may be concerned that there remains unobserved heterogeneity across states that is correlated with the relative wage of high skill workers and/or the relative supply of skills. Possible sources of correlated heterogeneity include higher demand for ICT-intensive products in higher-income states, variation across states in the price of capital or other factors, or unobserved variation in infrastructure or other environmental factors that are complementary with ICT. In the absence of convincing instruments for the relative supply of skills it is not possible to completely rule out alternative hypotheses, but in this section I attempt to address these concerns by including additional firm and state-level controls.

Tables 12 and 13 present these robustness results for the two countries, with the percentage of non-production workers using PCs as the dependent variable. Column (1) in each case includes further state level controls for the full sample: for Brazil the only additional control is the log of state income per capita in 2003, while in India both the log of state income per capita in 2000 and a state-level measure of the average number of days disrupted by power outages or surges from the national grid in 2001 are included.[41] Basant et al (2008) show that this latter variable appears to be correlated with firms' perceptions of the quality of infrastructure across Indian states, and thus it may help to control for variation in the price of energy and other potential complementary factors.

Consider first the Brazilian results in column (1) of Table 12, which can be directly compared to those in column (1) of Table 10. The coefficients on the two measures of the relative wage in Rows A and B are slightly smaller than those in Table 10, but the coefficient in Row B remains negative and highly significant. However, the results using direct measures of the relative supply of skilled workers in Rows C and D are very different once we control for the log of state income per capita, with none of the coefficients being significant, and the coefficient on the percentage with a college education becoming negative. The log of state income per capita is extremely highly correlated across states with the college share, with a correlation coefficient of 0.87 that is significant at the 1% level. Thus it is not possible to identify separately a positive

[41] See Appendix B for variable definitions.

effect of the college share on ICT adoption once log state income per capita is included as a regressor.[42] This may still be consistent with ICT adoption being skill-biased, since state income per capita may itself be a reflection of the supply of skilled workers. However, it does suggest that for Brazil it is not possible to rule out alternative explanations based on other unobservable factors that are correlated with income per capita.

As before, Rows E and F present IV specifications where the relative wage of more educated workers is instrumented by the education measures. The coefficient on the relative wage again becomes more negative in Row E but is only significant at the 10% level, while when the additional instrument is included in Row F the coefficient this time becomes insignificant. The main reason for these weaker results appears to be that the instruments have less explanatory power conditional on log state income per capita, with F-statistics of only 3.65 and 7.91 respectively.

The Indian results are less sensitive to controlling for additional state-level controls, as shown in column (1) of Table 13, which can be directly compared to column (1) of Table 11. The OLS coefficients on the relative wage of non-production workers in Rows A and B become slightly smaller, and the coefficient excluding Delhi becomes insignificant. However, the education results are extremely similar to those in column (1) of Table 11, and the IV coefficients on the relative wage in Rows E and F are both more negative than the equivalent OLS coefficient in Row B and highly significant. The cross-state correlation between log state income per capita and the college share is similarly high to that in Brazil (with a correlation coefficient of 0.86) but in the case of India the college share appears to have more explanatory power, and log state income per capita does not enter significantly.[43] Overall the results in column (1) of Table 13 suggest that the main results for India are robust to controlling for income per capita and a measure of infrastructure quality across states.

As discussed in Section 3, data on capital stock are not available for all firms, particularly in Brazil. Column 2 of Tables 12 and 13 thus presents results without any

[42] Log state income per capita itself enters positively and significantly, with a coefficient (standard error) in Row C column (1) of 27.33 (9.19).

[43] The coefficient (standard error) on log state income per capita in Row C column (1) of Table 13 is 8.01 (12.90). The state mean number of days disrupted by power outages does not enter significantly either, with a coefficient (standard error) of 0.370 (0.515).

additional controls but on the reduced sample for which capital stock is available, while column (3) includes capital intensity as an additional control on the same reduced sample. The reduction in sample size is very large for Brazil, with the sample falling from 375 to 130 observations, while in India the reduction is from 453 to 366 observations when Delhi is included, and from 352 to 298 observations when Delhi is excluded.

The results for Brazil in column (2) of Table 12 are, not surprisingly, less precisely estimated than those in column (1) of Table 10, given the large reduction in sample size, but they are qualitatively similar, with negative coefficients on the relative wage in both OLS and IV specifications.[44] More importantly, the results are not significantly affected when capital intensity is included in column (3), and capital intensity does not enter significantly in any of the specifications. Column (4) also includes materials intensity and log state income per capita as additional controls on the reduced sample. The materials share does not enter significantly, while the effect of including state income per capita is similar to that in column (1), with slightly smaller coefficients on the relative wage, and significantly more negative coefficients on the college share.[45]

The equivalent results for India in columns (2), (3) and (4) of Table 13 are much less different from the baseline results due to the smaller reduction in sample size. As with Brazil the inclusion of capital intensity as an additional control makes very little difference, and capital intensity is never significant. Finally, the main results are again robust to including all of the additional controls in the reduced sample in column (4), with significant positive coefficients on the college share that are similar to those in column (1) of Table 11, and significant negative coefficients on the relative wage in Rows E and F that are more negative than the equivalent OLS coefficient in Row B. The combined effect for India of reducing the sample size and including all of the additional controls is to reduce the size of the IV coefficient on the relative wage in Row F column (4) of Table 13 to just over half of the equivalent coefficient in Row F column (1) of Table 11.

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[44] The IV coefficient in Row E of column (2) is extremely imprecisely estimated due to the low power of the single instrument on the reduced sample.

[45] The significant negative coefficients on the college share in column (4) of Table 12 are driven in this reduced sample by the states of Sao Paulo and Rio de Janeiro, which have a particularly high college share but not commensurately high levels of ICT adoption conditional on their levels of income per capita. If these two states are dropped from the sample the coefficient becomes positive and insignificant.

6 Conclusion

This paper has used a unique new data set to provide the first firm-level evidence on the skill-bias of ICT in developing countries. Two empirical approaches were adopted. First, detailed information on firms' adoption of ICT and the educational composition of their workforce at two points in time was used to estimate skill-share equations in levels and long differences. The results are strongly suggestive of skill-biased ICT adoption, with ICT able to explain up to a third of the average increase in the share of skilled workers in Brazil and up to one half in India. These results are robust to differencing in order to eliminate unobserved firm fixed effects.

However, concerns remain over the possible simultaneity of firms' decisions about technology choice and factor mix, so a second approach used variation in the relative supply of skilled workers across states within each country to identify the skill-bias of ICT. The log relative wage of skilled workers by state was used as the main measure of the relative supply of skills, supplemented by direct measures of education levels across states. The results are again consistent with skill-bias in both countries, and are mainly robust to various methods of controlling for unobserved heterogeneity across states. However, the results using direct measures of education levels for Brazil are not robust to controlling for the log of state income per capita, which is extremely highly correlated across states with education levels. The results for Brazil may still be consistent with ICT adoption being skill-biased, since state income per capita may itself be a reflection of the supply of skilled workers. However, it does suggest that for Brazil it is not possible to rule out alternative explanations based on other factors that are correlated with income per capita.

For both approaches, the magnitudes of the estimated effects are surprisingly similar for the two countries. Overall, the results in this Paper suggest that new developments in ICT are now diffusing rapidly through the manufacturing sectors of both Brazil and India, with similar implications for the demand for skills in two very different and geographically distant countries. This evidence is consistent with ongoing pervasive skill-biased technological change associated with ICT throughout much of the developed and developing world. As discussed in the introduction, the implications for future developments in inequality both within and between countries are potentially far-reaching.

Table 1: Descriptive statistics for the full sample

	Brazil				India			
	Mean	Median	s.d.	Obs.	Mean	Median	s.d.	Obs.
Employment	207	70	431	387	367	70	1074	476
% change in Emp	22.0	7.8	63.2	368	19.7	14.3	37.7	471
% change in Sales	57.8	25.0	128.0	294	31.8	23.1	56.5	447
Materials share	0.44	0.41	0.31	194	0.41	0.40	0.25	433
Wage share	0.22	0.16	0.25	195	0.09	0.05	0.14	446
Capital intensity	0.75	0.32	1.19	156	0.56	0.25	1.03	395

Notes: Levels are for 2003 and changes are for the 2-year period 2001-2003. A small number of outliers are excluded from the above calculations as follows: change in sales greater than 1000% over the two-year period; materials share greater than 2; wage share greater than 2, capital intensity greater than 10.

Table 2: Measures of ICT adoption in 2003

	Brazil				India			
	Mean	Median	s.d.	Obs.	Mean	Median	s.d.	Obs.
Workforce usage								
% of non-production workers using PCs	69.6	90	37.9	484	53.9	59	34.6	476
% of production workers using ICT-controlled machinery	23.3	10	31.2	468	15.3	6	23.3	473
Summary measures								
Adoption index	3.50	4	1.22	491	2.94	3	1.05	476
Usage index	11.64	12	3.48	461	10.71	10	3.36	473

Notes: for ICT capital as a % of sales a small number of outliers are excluded with ICT capital as a % of sales greater than 300%.

Table 3: Change in ICT adoption, 2001-2003

	Brazil				India			
	Mean	Median	s.d.	Obs.	Mean	Median	s.d.	Obs.
Workforce usage								
% of non-production workers using PCs	12.5	0	20.9	462	14.2	10	19.4	476
% of production workers using ICT-controlled mach.	9.0	0	19.5	456	6.7	0	14.5	472
Summary measures								
Adoption index	0.68	0	0.92	482	0.59	0	0.78	475
Usage index	1.39	0	2.26	448	1.69	0	2.34	473

Notes: for ICT capital as a % of sales a small number of outliers are excluded with ICT capital as a % of sales greater than 300% in either 2001 or 2003.

Table 4: Mean occupation and education shares, 2004

	Brazil		India	
	Mean %	s.d.	Mean %	s.d.
Production workers				
Occupation share	69.9	18.5	62.0	18.7
Of which:				
Less than Primary	5.9	14.4	5.4	18.7
Primary but not Lower Secondary	17.5	22.8	15.2	20.8
Lower Secondary but not Upper Secondary	32.7	25.8	21.5	23.2
Upper Secondary but not College	38.7	30.9	41.2	29.4
College	5.1	9.9	16.7	25.5
Admin and clerical workers				
Occupation share	19.1	12.5	21.4	11.2
Of which:				
Less than Primary	0.6	4.8	0.1	1.2
Primary but not Lower Secondary	1.3	5.9	0.9	5.8
Lower Secondary but not Upper Secondary	6.3	17.1	6.3	14.4
Upper Secondary but not College	57.2	32.1	16.1	21.8
College	34.6	31.4	76.6	30.1

Notes: for production workers the sample contains 335 observations in Brazil and 446 observations in India; for admin and clerical workers the sample sizes are 353 and 449 respectively.

Table 5: Mean % changes in education shares, 2001-2004

	Brazil		India	
	Mean	s.d.	Mean	s.d.
Production workers				
Less than Primary	-1.9	7.3	-0.8	5.3
Primary but not Lower Secondary	-2.2	9.5	-1.2	6.2
Lower Secondary but not Upper Secondary	0.4	10.8	0.2	6.6
Upper Secondary but not College	3.1	11.0	0.7	7.3
College	0.6	2.6	1.1	5.2
Admin and clerical workers				
Less than Primary	-0.3	3.5	0.0	1.0
Primary but not Lower Secondary	-0.2	2.3	-0.1	1.1
Lower Secondary but not Upper Secondary	-0.3	3.4	-1.7	6.9
Upper Secondary but not College	-2.2	11.3	-1.3	9.6
College	3.0	10.9	3.0	9.9

Notes: for production workers the sample contains 335 observations in Brazil and 446 observations in India; for admin and clerical workers the sample sizes are 353 and 449 respectively.

Table 6: Production workers, levels

Dep. var.: education shares, 2004	(1) Less than Primary	(2) Primary but not Lower Secondary	(3) Lower Secondary but not Upper Secondary	(4) Upper secondary but not College	(5) College or above
Panel A: Brazil					
Mean share (%):	5.9	17.5	32.7	38.7	5.1
% using PCs	-0.073	-0.139	0.102	0.103	0.007
	(0.023)***	(0.041)***	(0.041)**	(0.050)**	(0.012)
% using ICT mach.	-0.062	-0.137	-0.116	0.252	0.063
	(0.022)***	(0.033)***	(0.041)***	(0.051)***	(0.023)***
Adoption index	-2.606	-4.050	0.242	5.231	1.184
	(0.762)***	(1.096)***	(1.386)	(1.495)***	(0.484)**
Usage index	-0.961	-1.836	-0.825	2.826	0.796
	(0.275)***	(0.387)***	(0.483)*	(0.540)***	(0.165)***
Panel B: India					
Mean share (%):	5.4	15.2	21.5	41.2	16.7
% using PCs	0.021	-0.088	-0.052	0.100	0.019
	(0.025)	(0.032)***	(0.041)	(0.045)**	(0.036)
% using ICT mach.	-0.034	-0.124	-0.169	0.006	0.321
	(0.022)	(0.033)***	(0.045)***	(0.076)	(0.069)***
Adoption index	-0.163	-1.010	-1.009	1.967	0.214
	(1.069)	(0.893)	(1.428)	(1.711)	(1.406)
Usage index	-0.505	0.077	-0.856	0.730	0.553
	(0.249)**	(0.309)	(0.391)**	(0.498)	(0.430)

Notes: each coefficient is from a separate specification using one ICT measure; robust standard errors in brackets; the sample contains 335 observations for Brazil and 446 observations for India; all specifications also include industry, state, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 7: Admin & clerical workers, levels

Dep. var.: education shares, 2004	(1) Less than Primary	(2) Primary but not Lower Secondary	(3) Lower Secondary but not Upper Secondary	(4) Upper secondary but not College	(5) College or above
Panel A: Brazil					
Mean share (%):	0.6	1.3	6.3	57.2	34.6
% using PCs	-0.012	-0.030	-0.058	0.003	0.098
	(0.008)	(0.011)***	(0.032)*	(0.052)	(0.049)**
% using ICT mach.	0.001	-0.003	0.011	-0.071	0.061
	(0.005)	(0.012)	(0.027)	(0.056)	(0.053)
Adoption index	-0.481	-0.589	-0.941	2.623	-0.612
	(0.256)*	(0.241)**	(0.915)	(1.578)*	(1.474)
Usage index	-0.158	-0.206	-0.542	-0.445	1.351
	(0.100)	(0.115)*	(0.301)*	(0.576)	(0.515)***
Panel B: India					
Mean share (%):	0.1	0.9	6.3	16.1	76.6
% using PCs	0.001	-0.011	-0.015	-0.037	0.061
	(0.001)	(0.009)	(0.018)	(0.032)	(0.041)
% using ICT mach.	0.003	-0.007	0.017	0.014	-0.028
	(0.002)	(0.009)	(0.026)	(0.044)	(0.057)
Adoption index	0.115	0.135	0.991	0.786	-2.027
	(0.078)	(0.505)	(0.784)	(1.056)	(1.542)
Usage index	0.024	-0.109	-0.041	0.133	-0.007
	(0.034)	(0.089)	(0.217)	(0.287)	(0.421)

Notes: each coefficient is from a separate specification using one ICT measure; robust standard errors in brackets; the sample contains 353 observations for Brazil and 449 observations for India; all specifications also include industry, state, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 8: Production workers, three-year difference 2001-2004

Dep. var.: change in education shares, 2001-2004	(1) Less than Primary	(2) Primary but not Lower Secondary	(3) Lower Secondary but not Upper Secondary	(4) Upper secondary but not College	(5) College or above
Panel A: Brazil					
Mean change (%):	-1.9	-2.2	0.4	3.1	0.6
% using PCs	-0.041	-0.021	0.012	0.045	0.005
	(0.022)*	(0.024)	(0.024)	(0.025)*	(0.007)
% using ICT mach.	-0.026	-0.000	-0.031	0.036	0.022
	(0.021)	(0.017)	(0.021)	(0.025)	(0.013)
Adoption index	-0.147	-0.882	0.325	0.484	0.220
	(0.488)	(0.537)	(0.600)	(0.738)	(0.184)
Usage index	-0.578	-0.330	0.029	0.650	0.229
	(0.232)**	(0.228)	(0.237)	(0.266)**	(0.103)**
Panel B: India					
Mean change (%):	-0.8	-1.2	0.2	0.7	1.1
% using PCs	-0.018	0.001	0.016	-0.003	0.004
	(0.015)	(0.020)	(0.016)	(0.028)	(0.011)
% using ICT mach.	-0.022	-0.048	-0.007	0.028	0.050
	(0.016)	(0.024)**	(0.024)	(0.032)	(0.019)***
Adoption index	0.074	-0.542	-0.575	0.932	0.112
	(0.374)	(0.456)	(0.481)	(0.535)*	(0.320)
Usage index	-0.024	-0.180	-0.299	0.318	0.185
	(0.106)	(0.133)	(0.136)**	(0.171)*	(0.096)*

Notes: each coefficient is from a separate specification using one ICT measure; robust standard errors in brackets; the sample contains 335 observations for Brazil and 446 observations for India; all specifications also include industry, state, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 9: Admin & clerical workers, three-year difference 2001-2004

Dep. var.: change in education shares, 2001-2004	(1) Less than Primary	(2) Primary but not Lower Secondary	(3) Lower Secondary but not Upper Secondary	(4) Upper secondary but not College	(5) College or above
Panel A: Brazil					
Mean change (%):	-0.3	-0.2	-0.3	-2.2	3.0
% using PCs	-0.021	-0.005	0.000	-0.001	0.026
	(0.013)	(0.007)	(0.008)	(0.029)	(0.030)
% using ICT mach.	-0.008	-0.004	0.002	-0.044	0.053
	(0.006)	(0.005)	(0.005)	(0.033)	(0.034)
Adoption index	0.182	0.025	0.022	-1.282	1.053
	(0.206)	(0.066)	(0.132)	(0.659)*	(0.639)
Usage index	-0.134	-0.113	0.059	-0.655	0.844
	(0.108)	(0.095)	(0.098)	(0.293)**	(0.267)***
Panel B: India					
Mean change (%):	0.0	-0.1	-1.7	-1.3	3.0
% using PCs	0.001	-0.001	-0.040	-0.002	0.042
	(0.002)	(0.002)	(0.017)**	(0.021)	(0.023)*
% using ICT mach.	-0.001	-0.002	-0.062	0.024	0.042
	(0.003)	(0.003)	(0.029)**	(0.052)	(0.054)
Adoption index	0.151	-0.015	-0.793	-0.031	0.689
	(0.170)	(0.103)	(0.438)*	(0.546)	(0.579)
Usage index	-0.025	0.027	-0.468	0.170	0.296
	(0.018)	(0.021)	(0.191)**	(0.241)	(0.227)

Notes: each coefficient is from a separate specification using one ICT measure; robust standard errors in brackets; the sample contains 353 observations for Brazil and 449 observations for India; all specifications also include industry, state, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 10: Relative wages, education and ICT adoption across Brazilian states

	(1)	(2)	(3)	(4)
Dependent var:	% using PCs	% using ICT mach.	Adoption index	Usage index
A. Log relative wage	-24.251	7.107	0.385	0.287
(in sample)	(15.717)	(7.486)	(0.460)	(0.802)
B. Log relative wage	-81.303	4.211	0.506	-1.602
(external data)	(15.051)***	(10.751)	(0.553)	(1.425)
C. Education				
% with college	5.682	-0.311	0.006	-0.094
	(1.481)***	(1.173)	(0.065)	(0.113)
D. Education				
% one year or more	1.673	-0.879	-0.019	0.009
	(0.737)**	(0.621)	(0.024)	(0.092)
% with college	1.532	1.870	0.053	-0.117
	(1.789)	(1.800)	(0.091)	(0.293)
E Log relative wage	-158.899	22.304	-0.774	2.132
(external data, IV)	(83.543)*	(37.585)	(2.298)	(4.579)
F. Log relative wage	-83.608	16.784	0.206	-1.174
(external data, IV)	(16.311)***	(18.353)	(0.695)	(2.242)
Hansen J-test	1.747	0.027	0.234	0.476
(p-value)	(0.186)	(0.870)	(0.629)	(0.490)

Notes: robust standard errors in brackets clustered by state, apart from statistical tests where robust p-values are in brackets; the sample for all specifications contain 375 observations across 13 Brazilian states; all specifications also include industry, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; row A uses the in-sample measure of the state log mean relative wage of non-production workers; row B uses the external measure of the log mean relative wage of workers with 11 or more years of education; row C uses the proportion of the population with college education, equivalent to 15 or 16 years of schooling; row D also adds the proportion with at least one year of schooling; in row E the external measure of the log relative wage is instrumented by the proportion of the population with college education, the robust F-statistic for the excluded instrument in the first stage is 3.41 and the partial R-squared is 0.116; row F adds the proportion with at least one year of schooling as a second instrument, the robust F-statistic for the two excluded instruments in the first stage is 17.80 and the partial R-squared is 0.697; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 11: Relative wages, education and ICT adoption across Indian states

	(1)	(2)	(3)	(4)
Dependent var:	% using PCs	% using ICT mach.	Adoption index	Usage index
A. Log relative wage	-41.572	-7.761	-0.786	-0.198
	(14.692)**	(6.355)	(0.391)*	(0.972)
B. Log relative wage	-36.933	-7.134	-0.765	-0.426
(excluding Delhi)	(11.450)**	(6.986)	(0.356)*	(1.111)
C. Education *(excluding Delhi)*				
% with college	17.261	0.190	0.408	0.588
	(3.757)***	(2.097)	(0.056)***	(0.223)**
D. Education *(excluding Delhi)*				
Literacy rate	0.142	0.570	0.005	0.050
	(0.679)	(0.272)**	(0.011)	(0.035)
% with college	16.059	-4.632	0.368	0.166
	(3.295)***	(2.662)	(0.104)***	(0.419)
E. Log relative wage	-70.476	6.000	-1.670	-2.187
(IV, excluding Delhi)	(22.771)***	(7.617)	(0.524)***	(1.494)
F. Log relative wage	-64.827	9.252	-1.520	-1.684
(IV, excluding Delhi)	(21.470)***	(7.333)	(0.561)***	(1.648)
Hansen J-test	0.950	0.949	1.151	1.501
(p-value)	(0.330)	(0.331)	(0.283)	(0.221)

Notes: robust standard errors in brackets clustered by state, apart from statistical tests where robust p-values are in brackets; the sample in Row A contains 453 observations across 9 Indian states; the sample in all other rows excludes Delhi and contains 352 observations across 8 Indian states; all specifications also include industry, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; rows A and B use the in-sample measure of the state log mean relative wage of non-production workers; row C uses the state proportion of the population with a college degree; row D also adds the literacy rate; in Row E the log relative wage is instrumented by the proportion of the population with a college degree, the robust F-statistic for the excluded instrument in the first stage is 16.84 and the partial R-squared is 0.560; row F adds the literacy rate as a second instrument, the robust F-statistic for the two excluded instruments in the first stage is 8.91 and the partial R-squared is 0.601; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 12: Robustness to controlling for capital and other controls, Brazil

Dependent var: % using PCs	(1) Full sample, state controls	(2) Reduced sample, no controls	(3) Reduced sample, K intensity	(4) Reduced sample, all controls
A. Log relative wage	-14.469	-48.286	-48.775	-45.674
(in sample)	(19.153)	(17.262)**	(17.733)**	(19.717)**
B. Log relative wage	-53.112	-38.061	-37.971	-29.088
(external data)	(22.031)**	(24.070)	(24.392)	(29.756)
C. Education				
% with college	-2.280	0.174	0.098	-11.541
	(2.930)	(3.293)	(3.403)	(4.257)**
D. Education				
% one year or more	0.180	1.517	1.514	-1.529
	(1.620)	(0.814)*	(0.825)*	(1.750)
% with college	-2.123	-2.963	-3.021	-12.579
	(3.535)	(2.979)	(3.030)	(5.012)**
E Log relative wage	-75.455	99.020	111.105	-460.234
(external data, IV)	(43.210)*	(164.892)	(168.188)	(658.116)
F. Log relative wage	-32.533	-61.429	-58.603	-23.490
(external data, IV)	(28.449)	(43.941)	(43.434)	(56.561)
Hansen J-test	1.316	0.833	0.946	4.661
(p-value)	(0.251)	(0.362)	(0.331)	(0.031)

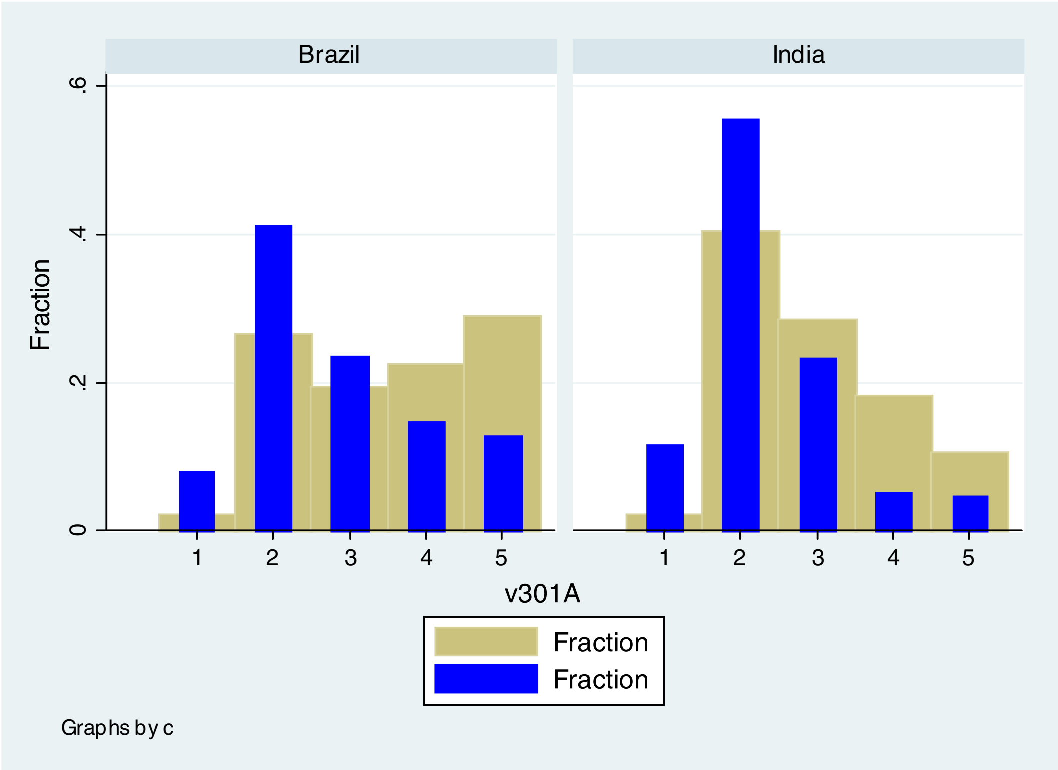
Notes: robust standard errors in brackets clustered by state, apart from statistical tests where robust p-values are in brackets; the sample in column (1) contains 375 observations across 13 Brazilian states; for all other columns the sample contains 130 observations across 12 Brazilian states; all specifications also include industry, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; additional controls are log state income per capita in column (1), capital intensity in column (3), and capital intensity, materials intensity and log state income per capita in column (4); the robust F-statistic for the excluded instrument in the first stage in Row E is 3.65 in column (1), 1.73 in column (2), 1.81 in column (3), and 0.51 in column (4); the partial R-squared is 0.231, 0.074, 0.075 and 0.063 respectively; the robust F-statistic for the two excluded instruments in the first stage in Row F is 7.91, 11.91, 12.63 and 9.58 respectively; the partial R-squared is 0.522, 0.604, 0.608 and 0.562 respectively; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively

Table 13: Robustness to controlling for capital and other controls, India

Dependent var: % using PCs	(1) Full sample, state controls	(2) Reduced sample, no controls	(3) Reduced sample, K intensity	(4) Reduced sample, all controls
A. Log relative wage	-34.787	-41.136	-40.909	-35.148
	(11.205)**	(12.603)**	(12.591)**	(9.840)***
B. Log relative wage	-16.972	-33.326	-33.336	-14.043
(excluding Delhi)	(9.356)	(8.200)***	(8.323)***	(8.724)
C. Education *(excluding Delhi)*				
% with college	16.114	15.424	15.426	14.502
	(4.115)***	(3.970)***	(3.970)***	(4.176)**
D. Education *(excluding Delhi)*				
Literacy rate	0.102	0.222	0.227	0.247
	(0.933)	(0.582)	(0.610)	(0.808)
% with college	15.968	13.497	13.457	14.033
	(3.281)***	(3.576)***	(3.860)**	(3.120)***
E. Log relative wage	-41.926	-63.200	-63.259	-38.269
(IV, excluding Delhi)	(19.405)**	(23.479)***	(23.497)***	(18.418)**
F. Log relative wage	-39.906	-58.437	-58.447	-36.481
(IV, excluding Delhi)	(16.761)**	(22.905)**	(22.924)**	(15.802)**
Hansen J-test	0.096	0.638	0.630	0.113
(p-value)	(0.757)	(0.425)	(0.427)	(0.737)

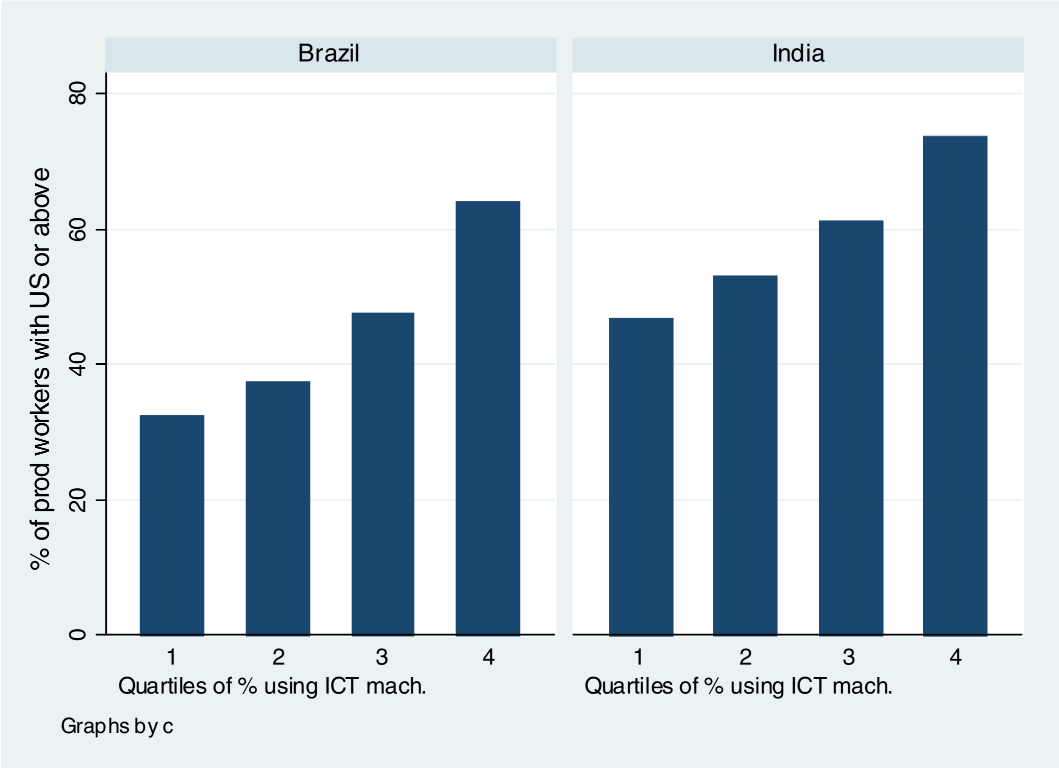
Notes: robust standard errors in brackets clustered by state, apart from statistical tests where robust p-values are in brackets; for column (1) the sample in Row A contains 453 observations across 9 Indian states, while the sample in all other rows excludes Delhi and contains 352 observations across 8 Indian states; for all other columns the sample in Row A contains 366 observations across 9 Indian states, while the sample in all other rows excludes Delhi and contains 298 observations across 8 Indian states; all specifications also include industry, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; additional controls are log state income per capita and state mean number of days disrupted by power disruptions in column (1), capital intensity in column (3), and capital intensity, materials intensity, log state income per capita and state mean number of days disrupted by power disruptions in column (4); the robust F-statistic for the excluded instrument in the first stage in Row E is 12.86 in column (1), 18.11 in column (2), 18.04 in column (3) and 12.86 in column (4); the partial R-squared is 0.497, 0.571, 0.571 and 0.533 respectively; the robust F-statistic for the two excluded instruments in the first stage in Row F is 6.43, 9.59, 9.58 and 6.25 respectively; the partial R-squared is 0.511, 0.604, 0.604 and 0.543 respectively.

Figure 1: Summary index of ICT adoption, 2001 and 2003



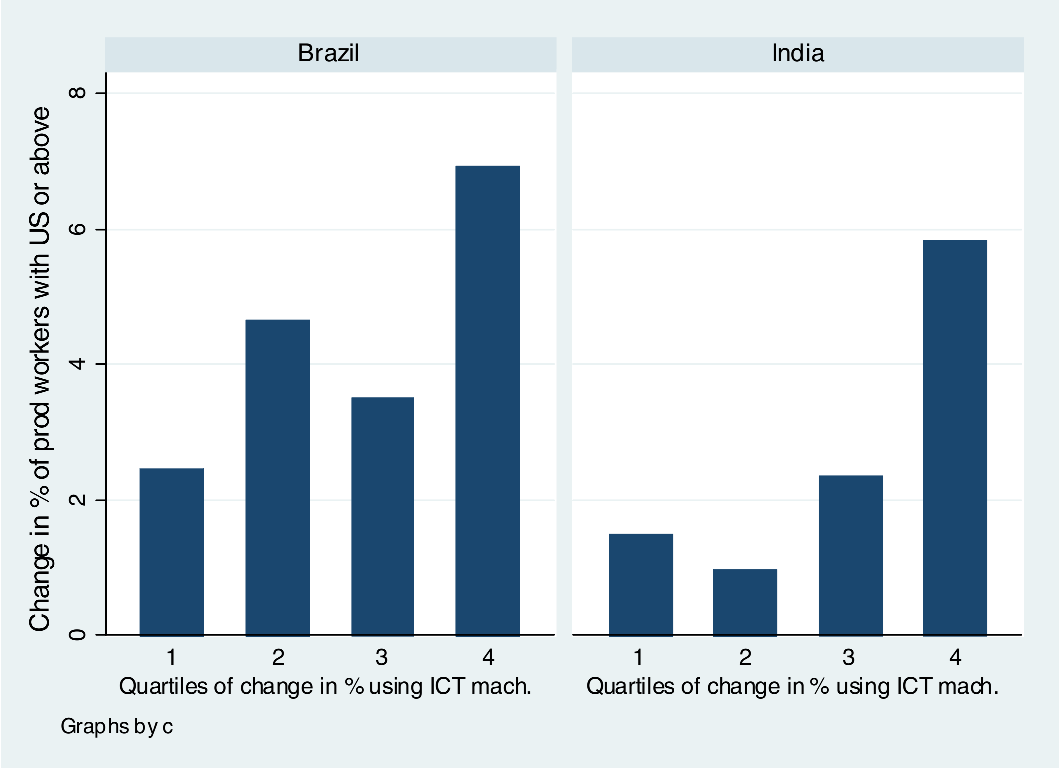
Notes: the vertical axis shows the fraction of the sample falling into each group; thin bars are for 2001, thick bars for 2003; details of variable construction are in the Appendix.

Figure 2: Production workers and ICT-controlled machinery, levels



Notes: the vertical axis shows the average percentage of production workers with upper secondary education or above for each quartile of the distribution of the percentage of production workers using ICT-controlled machinery on a daily basis as a part of their work; details of variable construction are in the Appendix.

Figure 3: Production workers and ICT-controlled machinery, differences



Notes: the vertical axis shows the average change in the percentage of production workers with upper secondary education or above for each quartile of the distribution of the change in the percentage of production workers using ICT-controlled machinery on a daily basis as a part of their work; details of variable construction are in the Appendix.

Figure 4: Relative wages and PC usage across Brazilian states

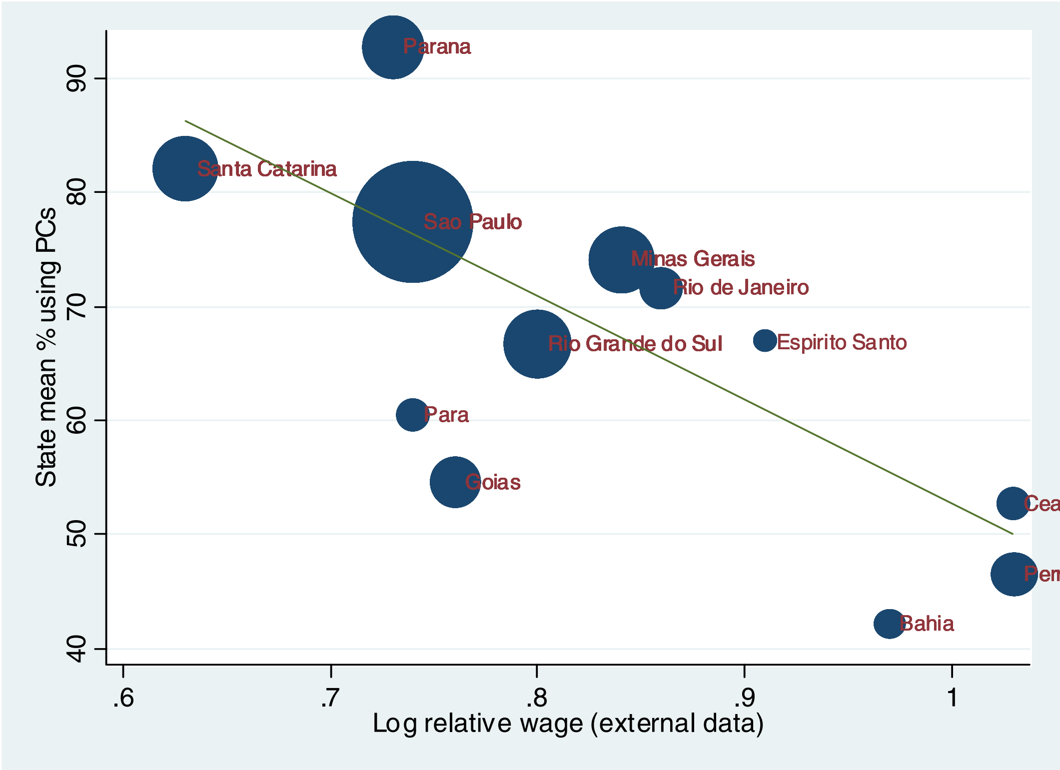
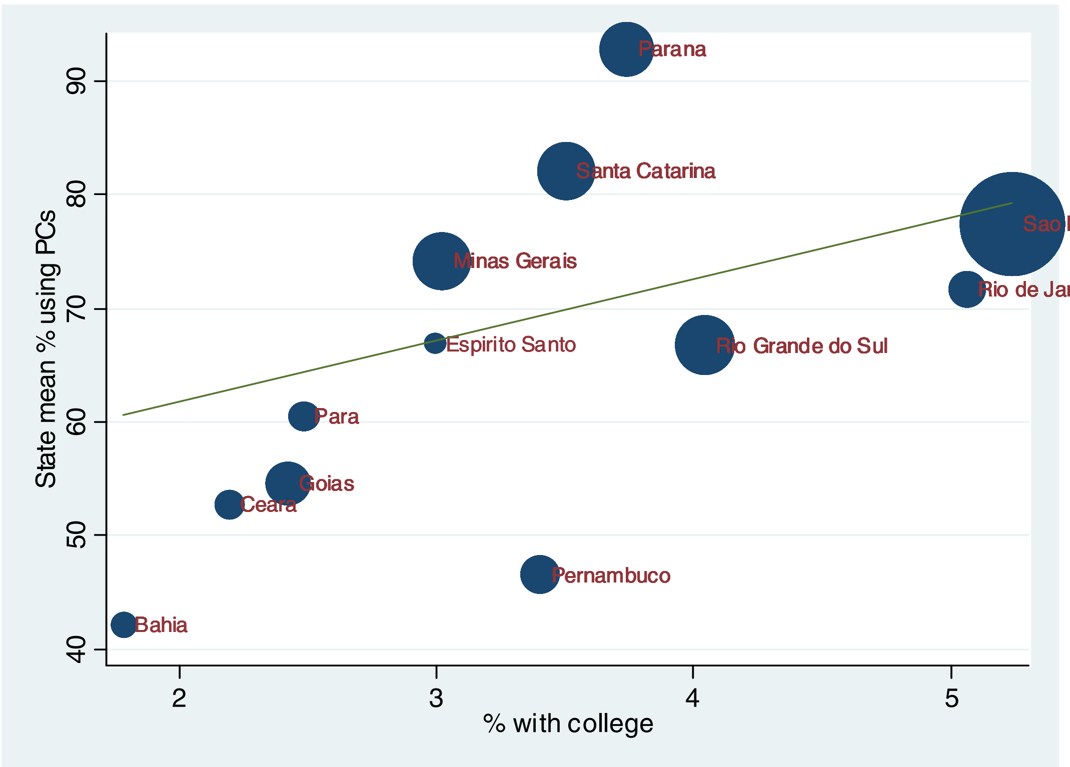


Figure 5: College education and PC usage across Brazilian states



Notes: the size of each circle is proportional to the number of observations in that state.

Figure 6: Relative wages and PC usage across Indian states

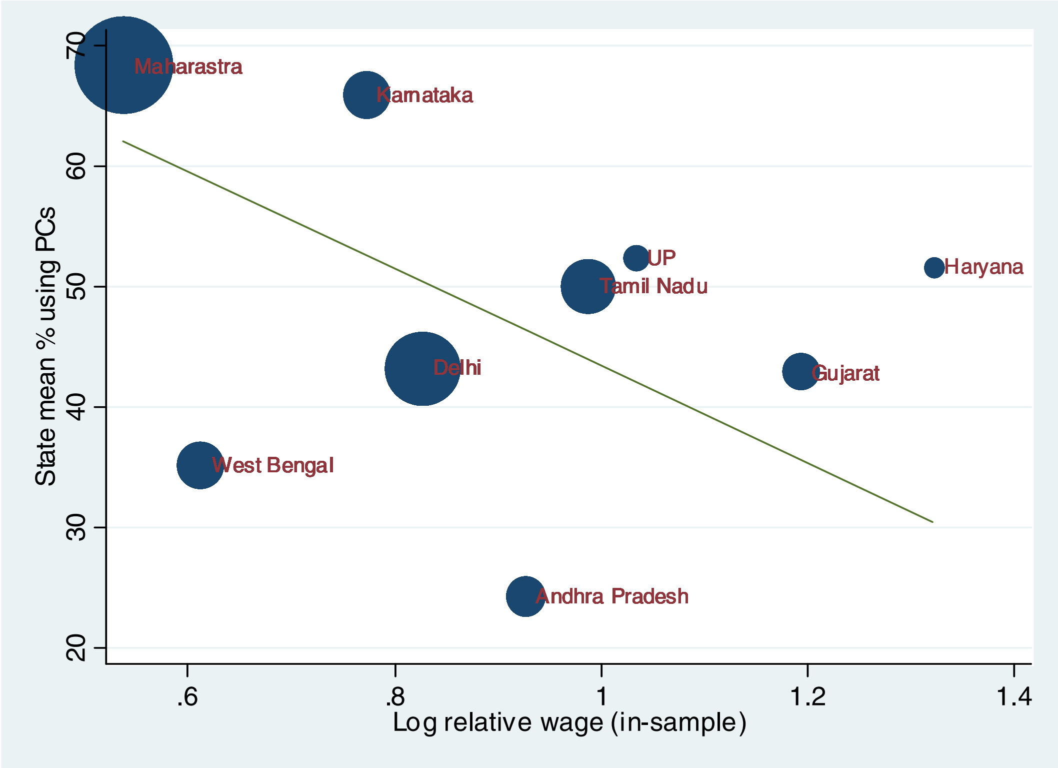
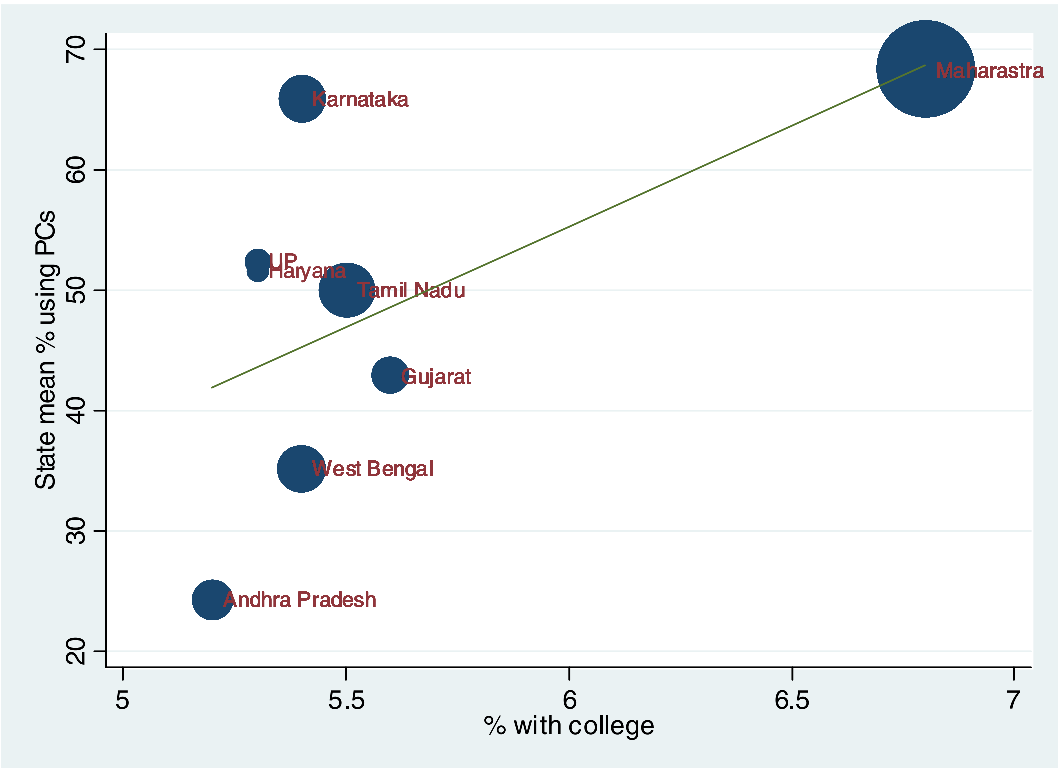


Figure 7: College education and PC usage across Indian states



Notes: the size of each circle is proportional to the number of observations in that state.

Appendix A: data collection

The survey was implemented for 500 firms in both countries between April and May 2005 through a series of face-to-face interviews. After an initial one-day training session, interviewers spent up to a day with each firm, with access to senior managers as well as human resources, ICT and finance departments. This was followed up with phone calls and repeat visits where necessary. The survey was designed following extensive testing and firm visits in each country.

The firms were selected in six 3-digit manufacturing industries: electronic components, plastic products, soap and detergents, auto-components, machine tools and wearing apparel. In India the sampling frame was a combination of the Prowess and First Source databases of accounts for firms registered with the Registrar of Companies, both collected by the Centre for Monitoring the Indian Economy (CMIE). Stratification was by industry, state and size (employment). The Prowess data set contains extensive financial data for mainly larger firms. The Prowess universe contained 437 firms in the chosen industries, of which 175 were sampled at random. The remaining 325 firms were taken from First Source, which is the largest financial database of firms in India. Data collection was organised in 14 regional centres located in nine states in India. In Brazil, the sampling frame was the official Industrial Census (Pesquisa Industrial Annual, or PIA). Stratification was again by industry, state and size (employment).

Table 14 gives the final distribution of the sample over states and industries. In India it was not possible to achieve a balance of firms across industries and states due to incorrect firm contact details and non-response. In Brazil, the number of observations in some states was below target quotas for similar reasons. In Brazil the ratio of refusals to responses was 3.4 while in India it was 4.5. No information was able to be collected on firms that refused. However, interviewers did not report any systematic differences between firms that refused and those that responded.

Appendix B: definition of ICT measures

% of non-production workers using PCs: constructed from answers to the question 'on average, what percentage of your non-production employees use PCs or workstations on a daily basis as part of their work, and what was the percentage three years ago (i.e. in 2001)?'

% of production workers using ICT-controlled machinery: constructed from answers to the question 'on average, what percentage of your production employees (non-managerial, but including supervisors and workers) use ICT-controlled machinery on a daily basis as part of their work, and what was the percentage three years ago (i.e. in 2001)?'

ICT adoption index: takes integer values from 1 to 5 inclusive according to answers to the question 'how would you describe the degree of ICT usage in your firm?' where the options were as follows: (1) ICT is not used at all; (2) ICT is used only for some office applications along with accessing the internet, emailing etc.; (3) ICT is used for some advanced applications, most processes are automated but there is no integration into a central system; (4) most processes are automated and some of them are integrated into a central system; (5) almost all processes are automated and integrated into a central system.

ICT usage index: takes integer values from 4 to 16 inclusive. For each of four functions (accounting services; inventory management; marketing and product design; production process) firms were asked 'how intensively does your firm use ICT for each of the following functions?' In each case the options were as follows: (1) do not use any ICT; (2) use ICT for some processes; (3) use ICT for most processes; (4) use ICT for all processes. The variable is constructed as the sum of these answers across the four different functions.

Appendix C: additional tables

Table 14: Sample distribution by state and sector

	Electronic Components	Plastic Products	Soap & Detergents	Auto Parts	Machine Tools	Wearing Apparel	*Total*
Brazil							
Amazonas	2	0	0	0	0	0	*2*
Bahia	0	2	5	0	1	3	*11*
Ceara	0	1	1	0	0	11	*13*
Espirito Santo	0	1	0	2	0	4	*7*
Goias	2	6	8	3	3	4	*26*
Minais Gerais	20	5	12	6	8	5	*56*
Parana	5	7	2	6	16	5	*41*
Para	0	4	2	1	0	3	*10*
Pernambuco	1	9	3	1	6	5	*25*
Rio de Janerio	4	7	6	4	7	6	*34*
Rio Grande do Sul	6	11	4	12	8	12	*53*
Santa Catarina	7	8	3	6	9	8	*41*
Sao Paulo	29	20	31	37	23	33	*173*
Total	*76*	*81*	*77*	*78*	*81*	*99*	*492*
India							
Andhra Pradesh	8	10	1	4	4	0	*27*
Delhi	14	22	10	27	5	23	*101*
Gujarat	2	15	2	1	1	4	*25*
Haryana	0	0	0	6	0	0	*6*
Karnataka	12	4	1	8	10	3	*38*
Maharashtra	25	56	22	32	17	22	*174*
Tamil Nadu	10	8	2	18	9	7	*54*
Uttar Pradesh	3	1	1	5	0	0	*10*
West Bengal	4	10	8	9	6	4	*41*
Total	*78*	*126*	*47*	*110*	*52*	*63*	*476*

Notes: figures show number of observations in each cell.

Table 15: Sector information for Brazil and India

	Electronic Components	Plastic Products	Soaps & Detergents	Auto Parts	Machine Tools	Wearing Apparel
India						
Share of manufacturing employment	0.5	1.9	5.8	2.2	1.9	4.6
Growth rates of employment (1998-2003)	-1.6	2.5	0.8	2.3	-3.3	3.7
Mean manufacturing wages (Rupees millions)	0.07	0.04	0.05	0.07	0.07	0.03
Growth rates of manufacturing wages (1998-2003)	10.6	5.7	4.4	14.2	1.8	7.6
Share of value added	0.9	1.7	11.0	2.5	2.2	2.0
Growth rates of value added (1998-2003	9.2	6.5	5.0	6.5	4.6	8.6
Growth rates of value added per worker (1998-2003)	10.6	12.3	5.2	8.0	3.6	-0.5
Brazil						
Share of manufacturing employment	1.0	6.1	4.7	5.8	6.8	5.4
Growth rates of employment (1998-2003)	9.4	33.3	18.2	23.3	31.8	13.5
Mean manufacturing wages (Reais 000)	9.1	6.8	10.9	12.3	8.3	4.9
Growth rates of manufacturing wages (1998-2003)	33.8	76.0	70.0	61.9	42.4	25.9
Share of value added	1.7	3.8	10.8	7.4	5.7	2.2
Growth rates of value added (1998-2003	-19.1	-11.4	-9.9	-12.2	-18.0	-12.7
Growth rates of value added per worker (1998-2003)	-12.6	-12.2	16.4	16.6	10.6	2.6

Source: Brazil: PIA, IBGE; India: Annual Survey of Industries.

Table 16: Country indicators for ICT, 2000 and 2004

	Brazil		India	
	2000	**2004**	**2000**	**2004**
ICT expenditure/GDP	5.6	6.7	3.6	3.7
Secure Internet servers (per 1m)	6.0	11.2	0.1	0.4
Telephone main lines (per1000)	182	237	32	43
Internet users (per 1000)	29	109	5	23
PCs (per 1000)	50	86	5	11
Broadband subscribers (per 1000)	0.6	12.8	0	0.6
International Internet bandwidth (bits per person)	5	154	1	4

Source: World Bank (2006)

Table 17: Production workers with controls, levels

Dep. var.: education shares, 2004	(1) Less than Primary	(2) Primary but not Lower Secondary	(3) Lower Secondary but not Upper Secondary	(4) Upper secondary but not College	(5) College or above
Panel A: Brazil					
(i) Without controls					
% using ICT mach.	-0.090	-0.212	-0.244	0.439	0.107
	(0.046)*	(0.060)***	(0.099)**	(0.093)***	(0.046)**
(ii) With controls					
% using ICT mach.	-0.087	-0.208	-0.250	0.436	0.109
	(0.046)*	(0.063)***	(0.101)**	(0.095)***	(0.041)***
Log capital	-0.682	1.565	-4.990	2.705	1.403
	(0.810)	(1.680)	(1.506)***	(1.903)	(0.481)***
Log value added	-0.649	-2.482	4.925	-0.124	-1.670
	(0.875)	(1.846)	(1.824)***	(2.160)	(0.697)**
Panel B: India					
(i) Without controls					
% using ICT mach.	-0.039	-0.116	-0.172	-0.038	0.365
	(0.023)*	(0.036)***	(0.047)***	(0.083)	(0.076)***
(ii) With controls					
% using ICT mach.	-0.035	-0.104	-0.172	-0.029	0.340
	(0.023)	(0.037)***	(0.049)***	(0.083)	(0.075)***
Log capital	0.391	-1.660	0.730	-0.093	0.633
	(0.451)	(0.526)***	(0.841)	(1.037)	(0.792)
Log value added	-0.682	0.114	-0.635	-0.845	2.048
	(0.621)	(0.973)	(1.073)	(1.380)	(1.070)*

Notes: robust standard errors in brackets; the sample contains 113 observations for Brazil and 349 observations for India; all specifications also include industry, state, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 18: Admin and clerical workers with controls, levels

Dep. var.: education shares, 2004	(1) Less than Primary	(2) Primary but not Lower Secondary	(3) Lower Secondary but not Upper Secondary	(4) Upper secondary but not College	(5) College or above
Panel A: Brazil					
(i) Without controls					
% using PCs	-0.004	-0.029	-0.016	-0.055	0.104
	(0.004)	(0.021)	(0.073)	(0.126)	(0.131)
(ii) With controls					
% using PCs	-0.004	-0.026	-0.006	-0.042	0.077
	(0.004)	(0.017)	(0.069)	(0.129)	(0.136)
Log capital	-0.031	-0.342	-1.705	2.715	-0.638
	(0.041)	(0.439)	(0.777)**	(1.969)	(2.133)
Log value added	0.017	0.068	0.763	-3.202	2.354
	(0.029)	(0.174)	(0.998)	(2.480)	(2.513)
Panel B: India					
(i) Without controls					
% using PCs	0.001	-0.013	-0.017	-0.030	0.058
	(0.001)	(0.012)	(0.021)	(0.037)	(0.047)
(ii) With controls					
% using PCs	0.001	-0.011	-0.013	-0.041	0.063
	(0.001)	(0.011)	(0.021)	(0.036)	(0.047)
Log capital	-0.013	0.098	0.401	-0.197	-0.289
	(0.027)	(0.148)	(0.457)	(0.635)	(0.958)
Log value added	0.053	-0.355	-0.921	1.609	-0.386
	(0.057)	(0.339)	(0.650)	(0.905)*	(1.319)

Notes: robust standard errors in brackets; the sample contains 119 observations for Brazil and 352 observations for India; all specifications also include industry, state, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 19: Production workers with controls, 3-year difference 2001-2004

Dep. var.: change in education shares, 2001-2004	(1) Less than Primary	(2) Primary but not Lower Secondary	(3) Lower Secondary but not Upper Secondary	(4) Upper secondary but not College	(5) College or above
Panel A: Brazil					
(i) Without controls					
Usage index	-0.173	-0.242	-0.237	0.589	0.064
	(0.250)	(0.665)	(0.617)	(0.296)*	(0.048)
(ii) With controls					
Usage index	-0.188	-0.103	-0.215	0.438	0.068
	(0.292)	(0.659)	(0.639)	(0.251)*	(0.053)
Log capital	-0.034	0.735	-0.875	-0.268	0.441
	(0.738)	(1.911)	(2.021)	(0.705)	(0.340)
Log value added	0.183	-1.849	-0.021	1.858	-0.172
	(0.684)	(1.441)	(0.788)	(1.137)	(0.113)
Panel B: India					
(i) Without controls					
Usage index	0.009	-0.219	-0.464	0.468	0.206
	(0.140)	(0.176)	(0.167)***	(0.228)**	(0.130)
(ii) With controls					
Usage index	0.005	-0.202	-0.455	0.483	0.169
	(0.137)	(0.174)	(0.162)***	(0.228)**	(0.124)
Log capital	-0.196	0.299	-0.296	-0.463	0.656
	(0.332)	(0.315)	(0.411)	(0.543)	(0.964)
Log value added	0.344	-0.744	0.164	0.238	-0.002
	(0.174)**	(0.423)*	(0.307)	(0.483)	(0.362)

Notes: robust standard errors in brackets; the sample contains 104 observations for Brazil and 330 observations for India; all specifications also include industry, state, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 20: Admin and clerical workers with controls, 3-year difference 2001-2004

Dep. var.: change in education shares, 2001-2004	(1) Less than Primary	(2) Primary but not Lower Secondary	(3) Lower Secondary but not Upper Secondary	(4) Upper secondary but not College	(5) College or above
Panel A: Brazil					
(i) Without controls					
Usage index	-	-	0.195	-1.505	1.310
	-	-	(0.166)	(0.583)**	(0.603)**
(ii) With controls					
Usage index	-	-	0.234	-1.639	1.405
			(0.196)	(0.602)***	(0.618)**
Log capital	-	-	-0.555	2.135	-1.580
			(0.588)	(1.541)	(1.611)
Log value added	-	-	-0.288	0.921	-0.634
			(0.358)	(1.292)	(1.315)
Panel B: India					
(i) Without controls					
Usage index	-0.022	0.038	-0.632	0.141	0.475
	(0.023)	(0.020)*	(0.278)**	(0.296)	(0.252)*
(ii) With controls					
Usage index	-0.021	0.040	-0.598	0.181	0.398
	(0.022)	(0.021)*	(0.276)**	(0.313)	(0.254)
Log capital	-0.007	-0.004	-0.476	0.017	0.470
	(0.014)	(0.019)	(0.506)	(0.525)	(0.594)
Log value added	-0.016	-0.045	-0.156	-0.886	1.104
	(0.026)	(0.045)	(0.391)	(1.081)	(1.014)

Notes: robust standard errors in brackets; the sample contains 109 observations for Brazil and 333 observations for India; all specifications also include industry, state, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; the lowest two education groups for Brazil do not contain enough observations with changing education shares to identify the coefficients; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 21: First stage regressions

Dep. var.: log relative wage	(1)	(2)
Panel A: Brazil		
% one year or more	-	-0.030
		(0.006)***
% with college	-0.031	0.043
	(0.016)**	(0.019)**
F-statistic	3.41	17.80
Partial R-squared	0.116	0.697
Panel B: India		
Literacy rate	-	0.012
		(0.008)
% with college	-0.234	-0.333
	(0.061)***	(0.101)**
F-statistic	16.84	8.91
Partial R-squared	0.560	0.601

Notes: robust standard errors in brackets clustered by state; the sample for Brazil contains 375 observations across 13 Brazilian states; the sample for India excludes Delhi and contains 352 observations across 8 Indian states; all specifications also include industry, size and age dummies, as well as controls for union membership, foreign ownership and joint ventures, listed status and state ownership; for each country column (1) contains the first stage for Row E of Tables 10 and 11, and column (2) contains the first stage for Row F; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 22: Relative wages and education levels by state

	(1) In-sample log relative wage of non-production workers	(2) Log relative wage of workers with 11+ years of education	(3) Literacy rate	(4) % with at least one year of education	(5) % with college education
Brazil					
Amazonas	0.92	0.69	-	72.7	1.5
Bahia	0.57	0.97	-	68.4	1.7
Ceara	1.54	1.03	-	68.9	2.1
Espirito Santo	0.55	0.91	-	75.5	2.9
Goias	0.64	0.76	-	75.3	2.4
Minais Gerais	0.93	0.84	-	76.9	3.0
Parana	0.54	0.73	-	77.7	3.7
Para	0.89	0.74	-	75.5	2.4
Pernambuco	0.92	1.03	-	71.7	3.4
Rio de Janerio	0.99	0.86	-	80.0	5.0
Rio Grande do Sul	0.82	0.80	-	81.4	4.0
Santa Catarina	0.81	0.63	-	82.3	3.5
Sao Paulo	0.82	0.74	-	81.3	5.2
Total	*0.83*	*0.79*	-	78.9	4.0
India					
Andhra Pradesh	0.93	-	50.0	-	5.2
Delhi	0.83	-	84.0	-	22.3
Gujarat	1.19	-	67.2	-	5.6
Haryana	1.32	-	66.2	-	5.3
Karnataka	0.77	-	58.1	-	5.4
Maharashtra	0.54	-	72.8	-	6.8
Tamil Nadu	0.99	-	69.8	-	5.5
Uttar Pradesh	1.03	-	51.3	-	5.3
West Bengal	0.61	-	63.4	-	5.4
Total	*0.75*	-	*70.73*	-	*9.5*

Sources: figures in column (1) calculated from in-sample information; other data calculated from household surveys and World Bank Education Statistics Database.

Bibliography

Acemoglu, Daron (2005), "Equilibrium bias of technology", MIT Department of Economics Working Paper 05-30

Aghion, P., Burgess, R., Redding, S. and F. Zilibotti (2006), "The Unequal Effects of Liberalization: Evidence from Dismantling the License Raj in India", NBER Working Paper No. 12031.

Attanasio, Orazio, Pinelopi K. Goldberg and Nina Pavcnik (2004), "Trade reforms and wage inequality in Colombia", *Journal of Development Economics*, 74(2), pp. 331-366.

Autor, David H., Katz, Lawrence F. and Alan B. Krueger (1998), "Computing Inequality: Have Computers Changed The Labor Market?", *The Quarterly Journal of Economics*, 113(4), pp. 1169-1213.

Autor, David H., Frank Levy and Richard J. Murnane (2003), "The Skill Content Of Recent Technological Change: An Empirical Exploration", *The Quarterly Journal of Economics,* 118(4), pp. 1279-1333.

Bartel, A.P. and Lichtenberg, F.R. (1987), "The comparative advantage of educated workers in implementing new technology: some empirical evidence", *Review of Economics and Statistics*, vol. LXIX, No. 1, pp. 1-11.

Bartel, Ann, C. Ichniowski and K. Shaw (2005), "How does information technology really affect productivity? Plant-level comparisons of product innovation, process improvement and worker skills", NBER Working Paper No. 11773

Basu, Susanto, Fernald, John G., Oulton, Nicholas and Srinivasan, Sylaja (2003), "The case of the missing productivity growth: or, does information technology explain why productivity accelerated in the United States but not the United Kingdom?" *NBER Macro-economics Annual*.

Berman, Eli (2000), "Does factor-biased technological change stifle international convergence? Evidence from manufacturing", NBER Working Paper No. 7964.

Berman, Eli, John Bound and Zvi Griliches (1994), "Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures", *The Quarterly Journal of Economics*, 109(2), pp. 367-97.

Berman, Eli, John Bound and Stephen Machin (1998), “Implications Of Skill-Biased Technological Change: International Evidence”, *The Quarterly Journal of Economics*, 113(4), pp. 1245-1279.

Berman, Eli and Stephen Machin (2000), “Skill-biased technology transfer around the world”, *Oxford Review of Economic Policy*, 16 (3), pp. 12-22.

Berman, Eli and Stephen Machin (2004), “Globalization, Skill-Biased Technological Change and Labour Demand”, in Lee, Eddy and Marco Vivarelli (eds.), *Globalization, Employment and Poverty Reduction*, International Labour Office, Geneva.

Berman, Eli, Rohini Somanathan and Hong W. Tan (2006), “Is skill-biased technological change here yet? Evidence from Indian Manufacturing in the 1990s”, World Bank Policy Review Working Paper 3671.

Bernard, A., J. B. Jensen and Peter Schott (2001), “Factor price equality and the economies of the United States”, NBER Working Paper No. 8068.

Bernard, A., S. Redding, P. Schott and H. Simpson (2002), “Factor Price Equalisation in the UK?”, NBER Working Paper No. 9052.

Besley, Timothy and Robin Burgess (2004), “Can Labor Regulation Hinder Economic Performance? Evidence from India”, *The Quarterly Journal of Economics*, 119(1), pp. 91-134.

Black, Sandra and Lisa Lynch, (2001), “How to compete: the impact of workplace practices and information technology on productivity”, *Review of Economics and Statistics,* August, pp. 434-445.

Bloom, Nick, Rafaella Sadan and John Van Reenen (2006) “It ain’t what you do, it’s the way you do I.T: Investigating the productivity miracle using US multinationals”, Centre for Economic Performance, April, mimeo.

Bound, John and Johnson, George (1992), “Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations”, *American Economic Review*, 82(3), pp. 371-92.

Breshnahan, Tim, Brynjolfsson, Erik and Hitt, Lorin (2002) "Information technology, workplace organization and the demand for skilled labor: firm-level evidence", *Quarterly Journal of Economics*, 117(1), pp. 339-76.

Brynjolfsson, Erik and Hitt, Lorin (2000), "Beyond computation: information technology, organisational transformation and business performance", *Journal of Economic Perspectives*, vol.14, no.4, pp. 23-48.

Brynjolfsson, Erik and Hitt, Lorin (2004), "Computing productivity: firm level evidence", *Review of Economics and Statistics*, 85(4), pp. 793-808.

Brynjolfsson, Erik, Hitt, Lorin and Yang, Shinkyu (2002), "Intangible assets: computers and organizational capital", *MIT Sloan* Paper 138.

Card, D. and J. E. DiNardo (2002), "Skill-biased technological change and rising wage inequality: some problems and puzzles", NBER Working Paper No. 8769.

Caroli, Eve and John Van Reenen (2001), "Skill-biased organisational change? Evidence from a panel of British and French establishments", *Quarterly Journal of Economics,* 116(4), pp. 1449-1492.

Caselli, Francesco and John Coleman (2001), "Cross-country technology diffusion: the case of computers", *American Economic Review: Papers & Proceedings*, May 2001

Chennells, Lucy and John Van Reenen (1999), "Has technology hurt less skilled workers? An econometric survey of the effects of technical change in the structure of pay and jobs", IFS Working Paper No. 99/27

Comin, Diego and Bart Hobijn (2004), "Cross-country technology adoption: making the theories face the facts", *Journal of Monetary Economics*, 51, pp. 39-83.

Doms, M., Dunne, T. and K. R. Troske (1997), "Workers, Wages, and Technology", *The Quarterly Journal of Economics*, 112(1), pp. 253-90.

Doms, M., Dunn, W., Oliner, S. and Sichel, D. (2004), "How fast do personal computers depreciate? Concepts and new estimates", *NBER Working Papers*, no.1010521.

Doms, Mark and Ethan Lewis (2006), "Labour supply and personal computer adoption", Federal Reserve Bank of Philadelphia Research Department Working Paper No. 06-10, June 2006

Dunne, Timothy, John Haltiwanger and Kenneth R. Troske (1997), "Technology and jobs: secular changes and cyclical dynamics", Carnegie-Rochester Conference Series on Public Policy, Elsevier, vol. 46, pp. 107-178.

Feenstra, Robert C. and Gordon H. Hanson (1996), "Globalization, Outsourcing, and Wage Inequality", *American Economic Review*, 86(2), pp. 240-45.

Geroski, Paul (2000), "Models of technology diffusion", *Research Policy,* 29, 603-625

Harrison, Ann and Gordon Hanson (1999), "Who gains from trade reform? Some remaining puzzles", *Journal of Development Economics*, 59(1), pp.125-154.

Harrigan, J. (1997), "Technology, Factor Supplies and International Specialization", *American Economic Review*, 87, pp. 475-94.

Hay, D.A. (2001), "The Post-1990 Brazilian Trade Liberalization and the Performance of Large Manufacturing Firms: Productivity, Market Share, and Profits", *Economic Journal* 111: pp. 620-641.

Katz, Lawrence and David Autor (1999), "Changes in the wage structure and earnings inequality", in Orley Ashenfelter and David Card, Eds., *Handbook of Labor Economics*, Vol 3A, Elsevier, New York and Oxford.

Katz, Lawrence F. and Murphy, Kevin M. (1992), "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", *The Quarterly Journal of Economics,* 107(1), pp. 35-78.

Keller, Wolfgang (2004), "International Technology Diffusion", *Journal of Economic Literature*, 42 (3), pp. 752-782.

Lal, Kaushalesh (2007), "New Technologies and Indian SMEs", *The ICFAI Journal of Applied Economics*, ICFAI Press, 0(1), pp. 20-41.

Leamer, Edward E. (1996), "Wage Inequality from International Competition and Technological Change: Theory and Country Experience", *American Economic Review*, 86(2), pp. 309-14.

Machin, Stephen (1996), "Wage Inequality in the UK", *Oxford Review of Economic Policy*, 12(1), pp. 47-64.

Motohashi, Kazuyuki (2005), "IT, Enterprise Reform and Productivity in Chinese Manufacturing Firms", Discussion papers 05025, Research Institute of Economy, Trade and Industry (RIETI).

Muendler, M. A. (2002), "Trade, Technology, and Productivity: A Study of Brazilian Manufacturers, 1986-1998", University of California, Berkeley, mimeo.

Pavcnik, N. (2002) "Trade Liberalization, Exit and Productivity Improvements: Evidence from Chilean Plants", *The Review of Economic Studies*, 69, pp. 245-76.

Pavcnik, Nina, Andreas Blom, Pinelopi Goldberg and Norbert Schady (2003), "Trade liberalisation and labour market adjustment in Brazil", World Bank Policy Research Working Paper No. 2982

Pohjola, Matti (2002), "The New Economy in Growth and Development", *Oxford Review of Economic Policy*, 18(3), pp. 380-396.

Sanchez-Paramo, Carolina and Norbert Schady (2003), "Off and running? Technology, trade and the rising demand for skilled workers in Latin America", World Bank Policy Research Working Paper

van Ark, B. R. Inklaar and R. H. McGuckin (2003), "The Contribution of ICT-Producing and ICT-Using Industries to Productivity Growth: A Comparison of Canada, Europe and the United States," International Productivity Monitor, Centre for the Study of Living Standards, vol. 6, pp. 56-63, Spring.

Van Reenen, John (1996), "The creation and capture of economic rents: wages and innovation in a panel of UK companies", *Quarterly Journal of Economics*, 443, pp. 195-226

World Bank (2006), *Information and Communication for Development: Global trends and Policies*, Washington DC