Endogenous Technology and Local Labor Market Skill

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Abstract

Despite the focus on the effects of new technologies and highly skilled workers in contributing to economic growth and explaining increasing wage inequality, the use of these new technologies and workers is not necessarily widespread. What is generating this heterogeneity? This paper proposes one answer: there is considerable geographic variation in the availability of skilled workers, and this variation in conjunction with labor market frictions forces firms to consider the skill mix of their local labor market before making an investment decision, thereby leading to endogenous technology. While previous studies of this phenomenon have focused on macro-level changes in the relative supply and demand of skilled labor, this paper utilizes cross-sectional variation in the availability of skilled labor in local labor markets to determine if otherwise similar firms invest differently in high technology capital depending upon the locally available skill mix. Employer-employee matched data is used to examine the relationship between an establishment's investment in high technology and local labor market skill while controlling for the firm's skill mix, industry and type. The results predict that a one standard deviation increase in local labor market skill will lead to roughly a 10% increase in technology investment, holding other characteristics of the firm constant. These results are robust to a series of different specifications including different measures of local labor market skill and definitions of the local labor market.

Despite the focus on the effect of new technologies and highly skilled workers in contributing to economic growth and explaining increasing wage inequality, the use of these new technologies and workers is not necessarily widespread. Previous research (Haltiwanger, Lane, Spletzer 2000 and Abowd, Haltiwanger, Lane, Sandusky 2001) shows that while many firms do appear to be utilizing the latest technologies and the most highly skilled workers, there are also many firms who have not adopted the latest technologies. Additionally, there is evidence that firms not choosing a high-technology strategy can be successful. Bresnahan, Brynjolffson, and Hitt (2002) find that firms using low levels of human capital and low levels of information technology are more productive than those investing in technology but not human capital or vice versa. While the overall trends, particularly in the 1980s, seemed to favor the use of more educated workers, there is heterogeneity behind that trend. What is generating this heterogeneity? This paper proposes one answer: the highly skilled workforce necessary to implement the latest technologies is not uniformly distributed across local labor markets and therefore endogenously influences a firm's technology investment decision.

Previous research in endogenous technology (Acemoglu (1998) and Kiley (2000)) focused on macro-level changes in the relative supply of skilled labor and its effect on technological change. This paper utilizes variation in the availability of skilled labor across local labor markets to determine if otherwise similar firms invest differently in high technology capital depending upon the locally available skill mix. The key difference between this research and the existing literature is that this paper exploits variation in a firm's investment decisions in a single cross section, while previous research has focused on time series trends in the development and implementation of new technologies. Identification in the cross section is complicated by the fact that the location decisions of both firms and workers are potentially endogenous. This problem is mitigated by focusing on an exogenous technological shock, the growth in the investment in computers in manufacturing between the early 1980s and 1990s. In the years between when the average firm made its location decision and the period in which the firm invested in computers, computer investment at manufacturing establishments increased rapidly. In contrast, the skill mix of the local labor market remained largely persistent over time. The introduction of a new technology to a set of existing firms aids identification of the effect of labor market skill on a firm's investment decision.

In addition to explaining heterogeneity in firm's investment choice, this paper is also closely related to the human capital spillovers literature. Following the taxonomy provided by Acemoglu and Angrist (2002), the literature on human capital externalities can be grouped into theories on non-pecuniary and pecuniary externalities. In theories on non-pecuniary externalities, spillovers occur through an exchange of ideas and are modeled by making firm productivity a function of aggregate skills in an area. Moretti (2004) directly estimates human capital spillovers using panel data and finds that firms in areas with a larger increase in the share of college graduates have a larger increase in productivity. In models of pecuniary externalities, such as the one used to motivate this paper, spillovers occur through firms' investment decisions. Empirical work on human capital spillovers does not distinguish between spillovers and endogenous technology.

The framework for the empirical work here is a two-period matching model based on a model in Acemoglu (1996). Firms know the distribution of workers in their local labor market, but not the worker with whom they will match when they make an investment decision.[1] This model sets up the two key equations for estimation: a wage equation and an investment equation. The wage equation takes advantage of a newly developed linked employer–employee data set and helps to quantify worker and firm heterogeneity. The investment equation uses results from the wage equation in conjunction with establishment level investment data from the 1992 Annual Survey of Manufactures to directly address the question laid out above: Do firms consider the skill mix of the local labor market before making a technology investment decision? Estimates of the effect of endogenous technology predict that a one standard deviation increase in local labor market skill will lead to roughly a 10% increase in technology investment. These results are robust to a series of different specifications including different measures of investment, local labor market skill, and definitions of the local labor market. The next section describes the model and the following section discusses the data. Section three discusses estimation, section four the results, section five robustness, and finally section six concludes.

1 The Model

The endogenous technology model developed here is a two period matching model similar to Acemoglu (1996). While Acemoglu's model focuses on social increasing returns to human capital, the search frictions in the labor market within his model can also be shown to lead to endogenous technology. Within the model developed here, the economy consists of a single autonomous local labor market and exists for two periods. While a full model of this economy would include multiple local labor markets

[1] Acemoglu (1999), Albrecht and Vroman (2002), and Eudey and Molico (2001) each develop models in which firms must decide upon the skill type of a vacancy before hiring workers. Firms therefore create vacancy types in reaction to the probability of being able to hire that type of worker.

and would allow for endogenous worker and firm mobility, here the larger economy can be thought of consisting of many local labor markets operating independently of one another. Workers vary in their skill level and are exogenously distributed across local labor markets. An individual worker's skill level is determined outside the model. This suggests that workers cannot adjust their skill level within the time frame of a firm choosing its investment level, i.e. a worker with a high school degree cannot obtain a college degree in the time a firm chooses and implements new technology. For simplicity in exposition, there are only two types of worker skill in the model, a high skill level and a low skill level. Extending the model to a continuum of skill types would not affect any of the important results of the model. Firms vary in their predetermined type and in the amount of their capital investment. There is a fixed marginal cost of capital equal to μ. Each firm employs only one worker.

The basic timing of the model is as follows. In period one, firms observe the distribution of workers in their local labor market, but do not know the type of worker with which they will match. The firm decides on a level of capital investment. In the second period, firms and workers are randomly matched to each other. Firms and workers must decide whether to continue with the match and produce or to remain idle for the period. Search costs create quasi-rents for the firm and worker within the match. If production takes place, returns to workers and firms are determined via a Nash bargaining solution. Workers receive a fraction B of match surplus and firms receive $1-B$, where $0<B<1$. Match surplus is equivalent to output in this model because the firm's first period investment is a sunk cost. Both workers and firms have zero opportunity cost, and it is assumed that output is nonnegative, implying that workers and firms will accept any division of match surplus and production will occur with all matches. Within this model, the Nash bargaining solution can be shown to be a general solution. The specific case in which *B* is equal to α, labor's share of income under constant returns to scale and Cobb-Douglas production, is equivalent to assuming that factors receive their marginal product.

Production takes place in worker/firm pairs

(1) $$Y_{ij} = A_j h_i^{\alpha} k_j^{1-\alpha}$$

where α is a value between 0 and 1, h_i is human capital for worker type *i*, k_j is firm *j*'s capital investment, and A_j is firm *j*'s idiosyncratic term which captures firm type, i.e. managerial ability, workplace organization, etc. Worker type *i* is equal to either 1 or 2, low skill level and high skill level respectively. A fraction ρ of workers are type 2.

In the second period, the realized returns for worker *i* and firm *j* are

(2) $$W(h_i, k_j) = BA_j h_i^{\alpha} k_j^{1-\alpha}$$

(3) $$R(h_i, k_j) = (1-B)A_j h_i^{\alpha} k_j^{1-\alpha}$$

Workers and firms receive share *B* and *1-B* of the match surplus. In the first period, firms and workers know the distribution of worker and firm types. Therefore, under rational expectations, workers' and firms' expectations in period one of their second period earnings are the expected value of the ex-post earnings.

(4) $$W(h_i, \{k_j\}) = Bh_i^{\alpha}(\int A_j k_j^{1-\alpha} dj)$$

(5) $$R(h_1, h_2, k_j) = (1-B)A_j((1-\rho)h_1^{\alpha} + \rho h_2^{\alpha})k_j^{1-\alpha}$$

The random matching process that occurs in the second period translates into uncertainty in the expected returns for both workers and firms in period one. Because workers don't know either the type or the capital intensity of the firm with which they will match, their expected returns depend on the entire distribution of firm types. Similarly, because firms don't know the skill level of the worker with whom they will match, their expected returns depend upon the distribution of worker types. Firms therefore make their investment decision in period one by equating the expected marginal return to capital investment to the marginal cost of capital.

(6) $$(1-B)(1-\alpha)A_j k^{-\alpha}((1-\rho)h_1^{\alpha}+\rho h_2^{\alpha})=\mu$$

This equation can be solved to find a closed form solution to the firm's investment decision.

(7) $$\Rightarrow k=\left(\frac{(1-B)(1-\alpha)A_j}{\mu}\right)^{1/\alpha}((1-\rho)h_1^{\alpha}+\rho h_2^{\alpha})^{1/\alpha}$$

Comparative statics show

(8) $$\frac{\partial k}{\partial A_j}>0 \qquad \frac{\partial k}{\partial \rho}>0$$

Therefore, the model suggests two main factors that will affect a firm's investment decision. A_j captures a firm's ex-ante heterogeneity. The higher A_j, the more likely a firm is to heavily invest in capital. Empirically A_j represents factors such as managerial ability or corporate culture that are inherent, semi-fixed characteristics of the firm.. ρ is the proportion of workers in the local labor market that is highly skilled. Firms located in more skill intensive areas should, according to the model, invest more in capital.

There are two key features of the model that lead to endogenous technology: capital-skill complementarity and search frictions. Capital-skill complementarities in the production function imply that a more skilled worker raises the marginal benefit of investing in capital. Therefore, if a firm knew with certainty the skill of the worker to which it would match in the second period, the optimal investment for the firm would increase with the skill of the worker. However, due to search frictions, the firm does not know the type of worker with which it will match when it makes its investment decision in the first period. Therefore, it bases its investment on the expectation of what that worker will be. If there are a large number of highly skilled workers in the local labor market, i.e. a high ρ, the probability that the firm will match with a highly skilled worker increases, and therefore the firm invests more heavily. If there were no search frictions, capital-skill complementarities would lead to a relationship between the skill level of the firm's labor force and the firm's technology choice. However, under this alternate scenario, there would be no relationship between a firm's technology choice and the skill mix of the local labor market after controlling for the firm's skill mix. Therefore, the empirical work can directly test if search frictions are generating endogenous technology.

2 Data and Measurement Issues

The data utilized in this research is well-suited to answer the question at hand. The employee employer matched data allows one to characterize the distribution of workers in a firm and to follow workers across employers. In addition, the Annual Survey of Manufactures provides information on the amount and type of establishment investment.

2.1 Workers

All of the data used in this research are taken from a three-state excerpt of the Longitudinal Employer-Household Dynamics program at the Census Bureau. Information on workers comes from the Unemployment Insurance (UI) wage records.[2] These files contain person identifiers that allow one to track a worker's earnings within a state over the available period.[3] The data also contain firm identifiers that allows for an exact link between the UI files and other data sets. The UI wage records contain approximately 95% of business employment for the states included in the analysis,[4] creating a final sample size of 198,644,076 observations representing 37,875,250 people and 3,989,740 firms. To obtain demographic information, administrative data is combined with the UI file providing date of birth and gender for all workers. As explained in detail below, the lack of other potentially important demographic information is econometrically handled by calculating a worker effect from a wage decomposition additionally controlling for the firm effect and time-varying characteristics.

The local labor market is defined by the place of work for employees. The model defines the local labor market as the region around a firm from which it can draw potential workers. Given workers' varying preferences for place of work, the current place of work is used to identify the places where a worker may potentially be interested in working. The county, rather than the metropolitan area, is used to define the local

[2] Three states were chosen on the basis of time-series availability at the time of project inception from the larger set of available states. A full list of the states available and additional information about the LEHD program is available at lehd.dsd.census.gov.
[3] Time periods vary by state, with the latest start date at 1991 and the earliest end date at 1998.
[4] The Unemployment Insurance program does not cover certain industries, i.e. agriculture and railroad transportation, nor certain employment types: self-employed workers, insurance agents classified as statutory employees, students employed by public universities, and non-profit organizations not participating in the UI program.

labor market. Metropolitan area definitions are created to capture a center of economic activity and the surrounding areas from which workers commute. However, because this analysis is based on where individuals work, the metropolitan area definitions are less relevant here. Also, as shown in previous research[5], there is statistically significant variation in county skill within metropolitan areas which aids in identification of the effect of local labor market skill.

The UI wage records contain identifiers for a worker's firm, but not his establishment. In order to create a measure of local labor market skill, each worker's skill needs to be assigned to a county. If a firm has establishments in multiple counties, it is impossible to determine in which establishment and therefore which county the employee works. While multi-unit firms only represent roughly 30% of employment for the states being studied, some algorithm must be used to allocate these workers' skills to a county. Additional information from the ES 202[6] files helps to alleviate this problem. The ES202 lists a firm identifier, an establishment identifier, the county and the number of employees at the establishment, but not the employee identifiers. From this data set, for each firm, the county in which that firm has the most employees is determined. The skill level of all workers of the firm are then attributed to that county. While it is impossible to determine which workers are properly assigned, 86% of the workers work in the county in which their firm has the most employees and are therefore correctly assigned.

[5] See Nestoriak (2004).
[6] The ES202 files are part of the Bureau of Labor Statistics Quarterly Census of Employment and Wages program. These data are provided to the LEHD program directly from the states.

2.2 Investment

Information on establishment investment comes from the 1992 Manufacturing Census. In 1992, the manufacturing Census included a series of detailed questions on capital expenditures for the Annual Survey of Manufactures (ASM) sample within the Census. The ASM disproportionately samples large establishments and provides sample weights to make the data representative of all establishments in manufacturing.[7] In addition to the sample weights, I also use the total value of shipments to weight the investment equation results in order to make the analysis representative of overall economic activity. The key measure of investment used here focuses on expenditures on computer equipment. Computer investment is divided by total equipment expenditures to create a measure of technology bias in an establishment's investment decision.

Computer investment data is only available in a single cross section. A potential problem with using a single period of investment is that establishments with zero investment in the data may be low technology firms, or they may be firms who invested heavily in the previous period. A few aspects of computer investment argue in favor of a large number of the zeroes being low-technology firms. The first is that computer equipment loses its value rapidly.[8] Therefore, in order to maintain a given value of computer stock, establishments need to invest substantially in computers in every year. The second aspect of computer investment that argues in favor of the zeroes being low-tech firms is the sharp increase in computer investment by manufacturing establishments

[7] The ASM sample consists of a certainty and a sampled component. The certainty component includes all establishments in companies with greater than $500 million in shipments in 1987, accounting for 18,000 establishments, and all establishments with greater than 250 employees, accounting for 10,000 establishments. The remainder of the 27,000 ASM establishments is sampled on the basis of establishment size and industry-level year-to-year volatility in shipments.

[8] Doms, Dunn, Oliner and Sichel (2004) estimate that computers lose half of their value in the first year of use. Most of this price decline is due to a fall in constant quality prices, with the remainder attributable to depreciation.

between 1982 and 1992. Dunne, Foster, Haltiwanger, and Troske (2004) measured the mean level of computer investment per worker in manufacturing to be $40 in 1982, $140 in 1987 and $830 in 1992. As a robustness check to the base estimation, the zero investors are grouped with small investors. Grouping the firms in this fashion assumes that truly high-technology firms invest significantly in every time period, but that it is impossible to distinguish between non-investors and small investors using the available data. A probit is then used to determine to what extent county level skill predicts whether firms are high technology firms, and these results are compared with those from the estimation based more directly on the model.

Both the Census investment data and the LEHD data have establishment information, but the two datasets have different establishment identifiers. The link between the data on investments and workers is available at an Employer Identification Number (EIN) level.[9] The EIN is an administrative unit that for a multi-unit business may be broader than an establishment and as large as a firm. For a single unit firm, the EIN is identical to the establishment. Therefore, the firm level characteristics calculated using the UI data, such as the firm effect and firm level human capital, are at an EIN level so that they can be matched to the investment data. However, because an EIN can have establishments in multiple counties, the EIN is not used for the firm investment data given that a goal of the analysis is to test the connection between an establishment and the local labor market skill of the county in which it is located. Instead, the investment data is aggregated to an EIN-county level, so that the investment numbers reflect data

[9] While the EIN is the only common identifier between the two datasets, there are other variables in common between the datasets, such as SIC, employment and payroll that could be used as an additional restriction on the match. Using additional restrictions, i.e. requiring that the EIN has the same SIC code in both datasets, has little effect on any of the results.

from all the establishments for a given EIN within a given county. This level of aggregation avoids trying to match establishments in the UI data to establishments in the Census data when the common identifier is an EIN. Using the EIN-county aggregate is equivalent to a single establishment for all but 5% of the observations.[10] In addition, in the analysis here, the key variable is the skill level of the county, thereby making an establishment level match unnecessary. Throughout the rest of this analysis, the EIN-county unit of aggregation will be referred to as the establishment.

3 Estimation

3.1 Wage Equation

The model assumes that wages are determined via rent sharing. This assumption, in combination with the form of the production function laid out in the model, implies that wages are a function of worker and firm characteristics. Because worker and firm heterogeneity influence the local labor market skill mix and firm investment decisions respectively, it is necessary to parameterize this heterogeneity before testing the main implications of endogenous technology laid out in the model. Population-based estimates of worker and firm heterogeneity can be determined via a wage decomposition. Taking advantage of what is available in the data, the equation used in estimation is

$$w_{ijt} = \theta_i + X_{it}^{'}\beta + \psi_{j(i,t)s} + \varepsilon_{ijt} \qquad (9)$$

This decomposition of wages is a variation on the methodology developed by Abowd, Kramarz, and Margolis (1999). Human capital is captured in the fixed worker effect, θ, and a quadratic in experience captured within *X*. Firm characteristics are

[10] With computer investment as a percentage of equipment investment as the dependent variable, 95% of the observations are single establishment EIN-county level observations.

captured in the limited time varying firm effect, ψ. The remaining variables contained in X are a series of gender by year by labor force attachment status dummies added to control for assumptions necessary to create an annualized wage measure from the quarterly earnings data. These variables also control for the observable time-varying characteristics.

Worker's wages also depend on the firm's type and the type of technology being used at the firm. A measure of firm type is needed as a control in the investment equation for the periods prior to investment when the firm is making its investment decision. A fixed effect is inappropriate because it will be contaminated with the current investment decision. While firm technology could vary period to period, suggesting fully time-varying firm effects, capital investment data is only available in two years, 1992 and 1997.[11] Therefore, a limited time-varying firm-effect is used. The three sub-periods chosen are as follows: 1991 and earlier (the period before the first investment), 1992 through 1996 (the period before the second investment), and 1997 on (the final period). The three firm effects are identified separately by the observations for that firm within that time period only. Although the firm effects are not generated in a manner which forces them to be correlated over time, analysis of the results from the wage equation show a correlation of approximately 0.7 between firm effects for the same firm across adjacent sub-periods. These results suggest that a component of the firm effect is fixed, and, therefore, that the limited-time varying firm effect is an appropriate way to capture firm heterogeneity in the periods prior to investment.

[11] Investment data are generally only available during Census years. In this paper, the 1992 computer investment data and the 1992 and 1997 equipment investment data are used. Computer investment data are not available in 1997.

Due to the large sample sizes, the wage equation is estimated separately for each state using the conjugate gradient methodology as explained in Abowd, Creecy, and Margolis (2002). The results are then pooled across the states included in the analysis, properly adjusting the person and firm effects to control for differences in state level mean wages. Identification of the person and firm effects is then determined by applying a grouping algorithm to the pooled state data. A connected group is determined by taking a firm, then pooling all of the employees of that firm, then taking all of the firms those employees ever worked at, then pooling all employees at the larger set of firms, and so on. The connectedness of the data is generated by the mobility of workers across firms. Within each connected group all but one person or firm effect is identified. For the group of states included, 99.9% of the observations are in one connected group.[12]

3.2 Investment Equation

The second equation to be estimated directly tests for endogenous technology at the establishment level. Comparative statics of the model suggest that a firm's technology decision should be increasing in firm type and, most importantly for endogenous technology, in the proportion of workers in the local labor market who are highly skilled. Combining information available from the ASM along with worker and firm heterogeneity terms from the wage decomposition, endogenous technology can be directly tested using

$$k_{jt} = \phi_0 + \phi_1 \psi_{jt-1} + \phi_2 s_{lt-1} + \upsilon_{jt} \tag{10}$$

[12] This group represents 99.1% of all workers and 89.3% of all firms in the pooled three state sample.

Taking the components of the equation one by one, k_{jt} is the technology investment variable; ψ_{jt-1}, the limited time-varying firm effect from the wage decomposition (9), is used as a proxy for firm type; and s_{lt} is local labor market skill, which is described below. In the model, k_{jt} is the stock of physical capital at the firm, and because the firm only exists for one time period, it is equivalent to investment in capital. Empirically, k_{jt} is measured as computer investment as a fraction of machinery investment.

Focusing on computer investment is ideal for a few reasons. The first is that capital skill complementarities are particularly strong with computers. Additionally, investment in computers can more readily be interpreted as a technology choice. Computers are a type of investment that is relatively homogenous across industries, and therefore, computer investment is likely to capture similar interactions between firms and workers across the range of industries within manufacturing. In a select group of manufacturing industries, Doms, Dunne and Troske (1997) find that although there is a positive correlation between skilled labor and the use of factory automation technologies in the cross section, an increase in the use of these technologies is not associated with an increase in the skill mix of an establishment's workforce. They argue that this pattern in the data suggests that firms choose a single technology/skill strategy rather than choosing different technology/skill strategies as they evolve. However, when focusing on computer investment, they do find that firms that invest more in computers do increase their share of non production workers. The authors argue that computers may be different than other measures of technology investment because they are more likely to be used by "overhead labor."

Finally, the growth in the use of computers around 1992 helps to argue in favor of the local skill level being exogenous to the firm. While in equilibrium one would expect that an establishment would choose a location, and therefore local labor market skill, suitable for their technology, the development of a new technology such as computers is an exogenous shock. The median age of a manufacturing establishment used in the analysis is 12 years. Most firms in the sample therefore made their initial location decisions on the technologies they expected to use over 10 years prior to 1992. In 1982, computer investment per worker in manufacturing was less than 1/20th its 1992 level.[13] When these firms entered the market, they most likely were unable to predict the change in the technologies that would be available to them, suggesting that their location decision was largely exogenous to the investment decision being studied here.

As mentioned above, the estimated firm effect from the wage decomposition is used as a control for firm type in the investment equation. While the model suggests that the firm effect would capture firm type, the firm effect is likely contaminated with other characteristics of the firm. In particular, given the assumption that wages are determined via rent sharing, the firm effect is also capturing aspects of the firm's technology. Because lags of the firm's technology are most likely correlated with their current technology investment decision, it is important to test the extent to which this misspecification might possibly bias the results. This issue is empirically addressed by including a lag of the capital stock per employee, or capital intensity, as an additional control in the investment equation. A more complete discussion and further justification for the empirical strategy can be found in Appendix A. As is shown in the results

[13] See Dunne, Foster, Haltiwanger and Troske (2000).

section, this specification problem does not appear to greatly affect the coefficient on county skill.

4 Results

4.1 Wage Equation

Table 1 summarizes the results of estimating equation 9 with limited time varying firm effects. Highlighting the key results, looking across the first row, the correlation of log wage with the worker effect is 0.56 and the correlation with the firm effect is 0.50. These results suggest that worker and firm effects are equally important in explaining the variation in log wages. The covariance between the worker and firm effects at the individual level is positive, although small in magnitude at 0.07. The positive covariance between worker and firm effects suggests that high skill workers are more likely to be at employed at high wage firms.

The results from estimating the wage equation are then used to quantify worker and firm heterogeneity. The fixed worker effect is used to capture worker skill and reflects any fixed characteristic of the worker that affects his wages. Although no individual level comparison of the worker effect and more traditional measures of skill are done here, Abowd, Lengermann, and McKinney (2003) have found that there is a positive correlation between the worker effect and education. Throughout the rest of the paper it is necessary to use functions of individual level skill to define either firm or local labor market level skill measures. While the thetas estimated at the individual level are inconsistent, functions of theta aggregated to the firm or county level are consistent.[14] The primary measure of county skill used throughout the paper, $\theta_l^{>75}$, calculates the percentage of workers within the firm or local labor market that are above the 75th percentile of the overall three-state distribution of the human capital measure in 1992.[15]

In order to identify the effect of local labor market skill in the investment equation, there must be variation across counties in skill. Figure 1 contains the kernel density estimate of the distribution of county skill measured by the percentage of workers in the county who are in the top quartile. The solid line represents the distribution in 1991, long dashes represent the distribution in 1995, and the small dashes represents the distribution in 1998. The density emphasizes the tremendous variation in county skill. In 1991, the least skilled county had 10% of its workforce in the top quartile while the most skilled county had 33% of its workforce in the top quartile. The distributions appear to be bi-modal with a second higher skilled mode being much smaller than the first. Comparing the densities across the three years represented, all counties are becoming more skilled over time.

In order for firms to be able to predict the skill available in the local labor market, there must be persistence in county skill. Additionally, if county skill is not persistent, then it seems more probable that firms are not limited to the type of workers currently in

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[14] Abowd, Kramarz, and Margolis (1999) show that for firm level averages of the person effect, $\hat{\theta}_j \equiv \frac{1}{N_j} \sum_{(i,t)\in\{J(i,t)=j\}} \hat{\theta}_i$, obey the asymptotic distribution $\hat{\theta}_j \to N(\theta_j, \sigma^2_{\theta_j})$ as $N_j \to \infty$ where N_j is the number of observations for firm j and $\sigma^2_{\theta_j} \equiv \frac{1}{N_j^2} \sum \frac{\sigma^2_\varepsilon}{T_i}$ under the assumption that the distribution of firm sizes is constant. Under these same asympotitics, θ_i will not converge to its true value.

[15] The 90th percentile was also used in earlier versions of this research and produced results similar to that of the 75th percentile.

their local labor market. Figures 2 and 3 study short and long term changes in county skill. The clustering of counties around the 45-degree line is, not surprisingly, very tight at the county level. Over the one year time horizon, the overall increase in skill translates into a fitted regression line that is a small parallel shift of the 45-degree line, emphasizing the persistence in variation discovered in earlier figures. Over the longer time horizon, the overall increase in skill results in a fitted regression line that is above the 45 degree line but also slightly less steep. While workers may be mobile, their mobility patterns reinforce preexisting distributions of skill across counties, thereby suggesting that establishments are limited to the type of workers found in their local labor market.

As an alternative to the county skill measures above, the fraction of workers in a county with a college degree can be computed from the Decennial Census. The correlation between the two county skill measures is high, with a correlation coefficient of 0.73. While the percentage of college graduates in a county is a simple, attractive measure of county skill, it also has disadvantages. The percentage of college graduates is calculated from responses to the long form of the Census and, as with every other survey, the data is subject to varying response rates by county and respondent error. In addition, the quality of the college attended, the major chosen, and the success of the student in school are not captured in this measure. The worker fixed effect, on the other hand, is a potentially richer measure of skill. It captures any attribute of a worker that is fixed and that is valued in the labor market, potentially including aspects of worker skill missed by the college graduate measure. While the exact components of what is encompassed in the worker fixed effect are unobservable, there are small differences between the different measures. Therefore, the usage of the worker effect to measure skill should produce results similar to more traditional skill measures, while capturing a richer definition of worker skill. An additional advantage of using the LEHD data to develop a skill measure is that it is possible to identify the firm for which a worker works and, therefore, additionally control for firm-level skill. However, as an additional robustness check, the percentage of college graduates by county is used as an alternative measure of local labor market skill.

4.2 Investment Equation

Before turning to the investment equation regressions, table 2 lists the summary statistics for the investment variables and results from the wage equation relevant to the investment analysis. The final sample for the investment analysis is the result of a match between the Annual Survey of Manufacturing sample of the 1992 Manufacturing Economic Census and the UI wage data for the selected three states. The level of aggregation for this sample is EIN-county. The final three rows highlight the effects of sample restrictions and weighting on the key independent variable, county skill measured as the percentage of workers in a county who are in the top quartile of the theta distribution. If one looks at the unweighted sample of counties, the mean county has approximately 20% of its workforce in the top quartile of the theta distribution with a variance of 0.05. Looking at the sample of firms that match to the computer investment data, the mean county skill is much higher at 25%. The mean county skill is higher in the matched sample because larger counties with more firms are more skilled. Weighting county skill by the product of the ASM sample weight and the total value of shipments has little effect on either the mean or variance of county skill.

Table 3 lists the results for the first set of regressions. There are six different specifications each including a different set of covariates. The first is the most basic specification including county level skill and the firm effect as calculated from the wage equation. The county skill measure used throughout the investment equation regressions omits the effect of the establishment's own employees on local labor market skill.[16] The second specification adds in firm level skill as a control, and the third includes both firm skill and industry dummies. Including firm level skill allows one to distinguish between the model outlined here and a competing model in which there are no search frictions. In this alternate model, firms would be able to meet a worker and then invest in technology leading to a positive coefficient on firm skill and an insignificant coefficient on county skill. Industry controls are necessary because industries locate non-randomly across geography. If highly skilled counties were comprised of industries that are more likely to utilize computers, again the county skill coefficient would be biased upward. Because the key independent variable varies by county but not by observation, robust standard errors based on clustering by county are included in parentheses.

The key coefficient of interest, the percentage of workers in a county who are in the top quartile adjusted for the establishment's contribution, is listed first. This coefficient is positive in each of the first three specifications. The magnitude of the coefficient on county skill diminishes as the additional control variables are added to the specification. In order to put an interpretation on the coefficient, the predicted percentage change in the dependent variable due to a one standard deviation increase in county skill is reported in the last row. In the third specification, the regression implies that a one

[16] The county skill measure excluding the establishment's contribution is calculated by subtracting the measure of *firm* (ein) skill weighted by the number of workers at that *establishment* (ein-county) from the overall county skill measure.

standard deviation increase in county skill leads to a 4.25% increase in the share of investment that is in computers. The other two independent variables in the first three specifications are the firm effect from the wage regression and firm level skill. The coefficient on the estimated firm effect is negative but not significant once industry controls are included, and the coefficient on firm skill is positive and significant in all of the specifications. Both variables have coefficients smaller in magnitude than county skill.

The specification in column 4 examines the effect of the most highly skilled county on the results. The existence of concentrations of establishments in like industries is well known. While the driving force behind these agglomeration economies may very well be their access to a pool of highly skilled labor and consistent with the theory laid out above, the success of these agglomeration economies may also be due to a myriad of factors not captured in the model. In order to determine if the results here are driven by a few agglomeration economies existing in highly skilled local labor markets, an interaction term between each of the key coefficients in the model and a dummy variable for the most highly skilled county was included in the fourth regression. The coefficient on county skill is still positive and significant, and the magnitude of the coefficient increases, suggesting that the predicted increase in the share of investment in computers from a one standard deviation increase in county skill is around 10%. The increase is likely due to the fact that the dependent variable is bound between zero and one. Regardless of its location, a firm can, at most, concentrate 100% of its investment in computers, but county skill on the other hand is unbounded. Therefore, removing the non linearity increases the magnitude of the coefficient on the bounded variable. Throughout most of the rest of the results, the interaction with the most highly skilled county is included. Whether or not the forces outlined in the model drive the effect of this most highly skilled county on the results, the inclusion of these interaction terms is necessary because the relationship between county skill and establishment investment in computers is non-linear due to this one county. The sensitivity of the results to such nonlinearities is further explored in the next section.

Columns 5 and 6 address a specification issue related to the estimated firm effect. While the model suggests that technology investment is influenced by firm type, a pure measure of firm type is not available. What is available is the estimated firm effect from the wage decomposition, which captures characteristics of a firm through their employee's wages. Under the assumption that wages are determined via rent-sharing, this firm effect should be a good proxy for firm type, but will be contaminated with other characteristics of the firm. In particular, if the estimated firm effect captures characteristics of the firm's previous technology decisions, and if these previous technology decisions are correlated with current technology investment, then the coefficient on the firm effect will be biased. The coefficient on county skill, the key variable for testing endogenous technology, will also be biased to the extent that county skill is correlated with the firm effect. In order to determine whether omission of previous technology investment affects the results, the 1991 capital stock is included as an additional covariate.

The capital stock measure is only available for a subset of the firms used in the earlier analysis. Column 5 repeats the specification in column 4 on this subset of firms. Column 6 includes the capital stock measure as an additional control variable. In the fifth column, the coefficient on county skill is slightly higher for the subset of firms for which capital stock information is available. Including the capital stock measure in column 6 slightly lowers the coefficient on county skill. This suggests that any potential bias from using the proxy for firm type and not controlling for the capital stock will be small. Given that the capital stock variable is only available for a subsample of the data, the results in the following tables rely on the full sample.

Due to the sensitivity of the results to one county, the preferred base specification is the fourth column of the table, which includes interaction terms with the most highly skilled county. These results suggest that a one standard deviation increase in county skill will lead to a 10% increase in the share of investment in computers. While these effects might seem large, a one standard deviation increase in county skill is equivalent to a five-percentage point increase in the number of workers in a county who are in the top quartile of the overall skill distribution. A five percentage point increase in skill, in which the average county has 25% of its workers in the top quartile, would require a significant reallocation of workers. Still, interpreting the results in this manner is helpful to gauge the importance of county skill in an establishment's investment decision. The effect of a firm's own skill mix, industry, and firm type are also important factors in an establishment's investment decision.

5 Robustness Checks

Because a variety of measurement and specification decisions underlie the results in table 3, a series of robustness checks are included below to test the sensitivity of the results to these assumptions. As is shown in detail below, the results in table 3 are robust to most of these decisions. In instances in which the results are sensitive, potential explanations are provided.

5.1 Nonlinearities

Given that the most highly skilled county greatly influences the coefficient on county skill, table 4 tests further for nonlinearities in county skill and offers a possible explanation. Column 1 repeats the base specification but includes no interactions with highly skilled counties. Column 2 is identical to the fourth column in the previous table and includes a full set of interactions with the most highly skilled county. The third column additionally includes interactions with the top 5% of most skilled counties which includes 8 counties. As shown earlier, the inclusion of interactions greatly affects the coefficient on county skill. In column three however, additional interactions with the top 5% of counties by skill are insignificant and do not change the coefficient on county skill greatly. The results therefore suggest that the nonlinearity with highly skilled counties is, for the most part, concentrated in just one county that happens to be the most skilled one.

The most highly skilled county is not an outlier in its skill level, which is not far removed from the rest of the distribution. Rather, this one county has both many skilled workers and high levels of computer investment. The final regression in table 3 highlights one potential characteristic of the highly skilled county that may be driving its impact on the results. In the fourth specification, the county's percentage of workers employed in high tech industries, SIC 35 and 36,[17] is included as a covariate. These results are similar to the prior regression that included the interaction terms with the most highly skilled county. As mentioned above, the impact of this one county may be due to

[17] SIC 35 and 36 are Industrial and Commercial Machinery and Computer Equipment; and Electronic and Other Electrical Equipment and Components, respectively.

aspects of agglomeration economies that are not captured in the endogenous technology model.

5.2 Weighting/Firm Size

The dependent variable in the previous tables requires use of the ASM to obtain information on expenditures on computers. This sample drawn from the Census of Manufactures is disproportionately composed of large firms and is not representative of all manufacturing establishments.[18] In order to make the results representative of the average manufacturing establishment, the results must be weighted by the Census ASM sample weight. However, the representative firm in manufacturing is rather small and therefore accounts for only a small fraction of the manufacturing industry's output. Due to this fact, all of the regressions in the earlier tables are weighted by the product of the Census ASM sample weight and the total value of shipments for that establishment in order to make the results representative of a given unit of economic activity.

Table 5 repeats the base specification using three different weighting patterns to highlight the effect of weighting on the results. In the first column no weights are used, in the second column the Census ASM weight is used, and in the third column the product of the Census ASM weight and the total value of shipments is used, as in the rest of the analysis. In the unweighted regression the predicted effect of a one standard deviation increase in county skill on the dependent variable leads to a 6% increase in computer investment divided by machinery investment. Weighting the same regression by the Census ASM weight makes the effect insignificant, and weighting by the product of the Census ASM weight and total value of shipments increases the effect to 10%.

[18] See details in footnote 7.

The differences in the effect of county skill on investment across the regressions is likely due to the differences in the explanatory power of different size firms. The unweighted sample is disproportionately composed of large firms, and the Census ASM weight corrects for that so that the results reflect the representative firm, which is much smaller. Finally, the product of the Census ASM weight and the total value of shipments shifts the emphasis back to larger firms again. Why does the effect of county skill seem to be larger for larger firms? This effect may be driven by a variety of reasons. First, computer investment at the establishment level is measured with less error in larger firms. The ASM is collected in order to publish aggregate statistics about manufacturing. Because larger firms will drive any aggregate statistic, more effort is focused on collecting data in these large firms. Second, there may be non-linearities in the relationship between county skill and establishment investment in computers. In part, this effect is driven by the fact that larger firms need to hire more workers. Earlier research has shown that in order to get the greatest productivity boost from introducing computers, establishments must integrate computers into much of their operations. Larger establishments with larger operations require more skilled workers in order to integrate computers. In addition, larger establishments invest more per worker than small establishments even when controlling for industry, the firm effect from the wage equation, and firm level skill.

5.3 Alternate Skill Measures

Table 6 tests the sensitivity of the results to different ways of measuring county skill. Column one repeats the base specification. Column two uses the percentage of workers in a county from the top quartile of the theta distribution by measuring human capital using the sum of the fixed worker effect and the predicted effect of experience from the wage regression. The effect of county skill is a bit larger when worker experience is included in the skill measure. The third column uses the mean theta in a county and the fourth column uses the mean of the sum of theta and experience. The effect of mean county skill is smaller when worker experience is included in the measure of skill.

Finally the fifth column uses the percentage of college graduates in a county calculated using the 1990 Census data. These results are remarkably close to that found in the base specification. There are a few differences between the specification in columns 1 through 4 and that in column five due to the differences in the underlying data: the specification does not include a control for firm level skill, the firm's contribution to the county skill measure is not excluded, and this measure of county skill utilizes 1990 data as opposed to 1991 data in the earlier specifications. Conceptually, the key difference between the college measure and the others is that the college measure is calculated using individual's responses about their education from the Census, while the other skill measures are derived from a wage regression using administrative data. While the differences between the results using the employer-employee matched data from LEHD and those using the Decennial Census data may be small, the matched data is necessary for two primary reasons. The first is that the magnitude of the results are deceptively large when using the Decennial Census measure because one cannot control for firm level skill. The second reason is that the firm effect can only be computed from the matched data, and it is a control in the investment equation. The small differences in the predicted change in the dependent variable due to a one standard deviation increase in the county skill measure across the five specifications suggests that the effect being found is not the result of a particular way of measuring skill. The results in the final column are the strongest support for this claim, given that they are calculated in a different way, from a different data source.

5.4 Alternate Local Labor Market Measure

County of work has been used as the measure of the local labor market throughout the analysis. While a county is a desirable measure of the local labor market for the reasons listed previously, the metropolitan area is also commonly used to define a local labor market. Table 7 includes a comparison between the base specification, in column 1, and one in which the local labor market is defined by the metropolitan area[19] in column 2. Because the metropolitan areas are not exhaustive, the county level skill measure is used in non-metro areas. Columns 3 and 4 exclude establishments in these non-metro areas. Whether or not the non-metro areas are included, the results are a bit smaller when the metropolitan area definition of the local labor market is used. The effect of a one standard deviation increase in local labor market skill is a bit misleading because there is less variance in metropolitan area skill than there is in county skill. Regardless, using the metropolitan area as the measure of the local labor market produces results very similar to those produced using county as the local labor market measure.

5.5 Probit

As mentioned above, the computer investment data used for this analysis comes from a single cross section. Implicitly, the estimation assumes that computers are a non-

[19] The metropolitan area used in this analysis is either the Metropolitan Statistical Area or the Primary Metropolitan Statistical Area of a Consolidated Metropolitan Statistical Area. For the states included here, there are 40 metropolitan areas.

durable. As a robustness check to the base specification, establishments are placed into a low investor and a high investor group, where the high investors are in the top quartile of computer investment as a share of machinery investment. Table 8 repeats the base specification, excluding firm skill in column one and with firm skill in column two, and shows the results of the probit without firm skill in column three and with firm skill in column four. The probit predicts that a one standard deviation increase in county skill will increase the likelihood that a firm is high tech by 18 to 24% depending on whether or not firm skill is included. While the results in columns three and four appear larger, the specifications are measuring different things and are impossible to directly compare. However, they do both suggest that county skill plays a role in computer investment.

5.6 Alternate Dependent Variables

As a final robustness check, machinery investment per worker is used as the dependent variable in table 9. Machinery investment is asked of all establishments in Census years, therefore the results using machinery investment per worker are computed for both years for which human capital data is also available, 1992 and 1997. The results in Panel A, machinery investment per worker in 1992, and in Panel B, machinery investment per worker in 1997, both follow the same broad pattern. The first specification uses theta as the measure of county skill. The second also uses theta and additionally includes interactions between the key coefficients and the most skilled county. The third uses the sum of theta and worker experience to measure county skill and the fourth adds in interactions with the most skilled county. Contrary to the earlier results using computer investment as the dependent variable, the coefficient on county skill is negative in the first two specifications of either panel, suggesting that firms in counties with large numbers of workers with high worker effects are less likely to invest in machinery. However, the coefficient is positive, yet still not significant, in the last two specifications, in which county skill is measured using the sum of the worker effect and worker experience. The difference in the pattern in these results compared to the earlier results using computer investment is likely due to the fact that machinery investment is very heterogeneous. While machinery investment includes computer investment, it is also comprised of much older technologies, which may be more complementary to worker experience and be a substitute for other worker skills. Another difference between the results in this table and the earlier results is that removing the affect of the most highly skilled county does not impact the results. This finding suggests that the nonlinearities associated with the most highly skilled county are limited to computers and do not apply to investment more generally.

6 Conclusion

There is tremendous heterogeneity in the technology employed by firms, even in narrowly defined industries. One potential cause of this heterogeneity is endogenous technology driven by the variation and persistence of human capital across different local labor markets. The research here builds a matching model capturing the effects of local labor market worker skill on establishment investment decisions. By taking advantage of a unique employer-employee matched dataset, the results begin to quantify the effects of local labor market skill on establishment technology.

The best estimates of the effect of county skill on an establishment's investment predicts that a one standard deviation increase in county skill will lead to a 10% increase in the investment share of computers for a representative unit of economic activity.

Weighting the results and thereby shifting the emphasis between smaller and larger firms does affect the results. The effect of an increase in county skill is not nearly as large for a representative establishment. This outcome suggests that county skill has a greater impact on the investment decisions of larger firms. However, the results are robust to different ways of measuring county skill, different measures of the local labor market, and different functional forms of the specification. The results are sensitive to the type of investment undertaken by the establishment. When county level skill is measured by including the effect of worker experience, one finds positive yet insignificant results with machinery investment per worker as the dependent variable, likely due to the fact that capital-skill complementarity is not as strong with machinery investment. The pattern found in the results is consistent with other research on technology adoption. Productivity enhancements from computer usage require widespread changes in an establishment. These changes require a large investment in skilled workers. The research here suggests that firms are more willing to make the investment in computers if the necessary workforce is available.

One area for further research is to explore how endogenous technology affects the dynamics of worker location. While the empirical work here uses investment in computers in a relatively early time period to ensure that workers are exogenously distributed in reference to firms' likelihood of investing in computers, data in later periods can be used to examine workers' reactions to firms' investments. The results here suggest that it is in the best interest of the high-tech firm and the highly skilled worker to locate in high skill areas. As technology usage increases in an area, does one also see an increase in the concentration of skilled workers?

Appendix A: Investment Equation Specification

The model suggests that the firm type needs to be included as a control in the capital investment equation. While a pure measure of firm type is not available, we do measure ψ, the firm effect from the wage equation, and use it in estimating equation 10. In order to get a handle on the extent of the potential bias due to this problem, it is first necessary to distinguish between capital investment and capital stock. Due to its limited dynamics, it is impossible to distinguish between investment and capital stock within the model. Empirically, however, it is likely that wages are influenced by the sum of previous period's investments of the worker's firm, or the capital stock. Keeping this distinction in mind, it is clearer if equation 10 is re-written as

$$I_{jt} = \phi_0 + \phi_1(\ln A_j^{1/\alpha} + \ln k_{jt-1}) + \phi_2 \hat{s}_{lt-1} + \upsilon_{jt}$$

in which the term in parentheses is the firm effect from the wage equation, I_{jt} is computer investment and k_{jt-1} is the capital stock in the previous period. This equation, which is the one that can be estimated with the available data, is misspecified due to the inclusion of lagged capital stock. The true equation can be re-written as

$$I_{jt} = \phi_0 + \phi_1(\ln A_j^{1/\alpha} + \ln k_{jt-1}) + \phi_2 \hat{s}_{lt-1} - \phi_1 \ln k_{jt-1} + \upsilon_{jt}$$

Written in this form, equation 10 has an omitted variable, k_{jt-1}. Given that k_{jt-1} is correlated with ψ and with s_{lt-1}, all of the coefficients in the model are potentially biased. While there is no available information on the stock of computer investment in the previous period, a measure of the stock of machinery equipment is available in 1991.[20] The stock of machinery equipment includes the stock of computer equipment, but is a much broader measure. While not the ideal measure, adding the capital stock variable will help to determine the extent to which the specification problem mentioned above is effecting the results, and in particular, the coefficient on county skill. Results are shown in the last column of table 3 and discussed in the text.

Additional biases to the results will occur if one assumes that computer investment is correlated over time in a way that is not captured by either the firm effect, the firm's skill level, nor the local labor market skill level, i.e. serially correlated technology shocks, such that

$$\upsilon_t = \lambda \upsilon_{t-1} + \eta_t$$

in which λ captures the serial correlation and η is the current period innovation. The coefficient on the firm effect in the original specification will be biased upward because, as shown above, the firm effect contains information on the previous period's investment,

[20] For details on the creation of this variable see Chiang (2003). The basic methodology involves using the reported capital stock measure in Census years and applying the perpetual inventory method for non-Census years.

which will be positively correlated with the serially correlated component of the error term.

To some extent, the inclusion of the capital stock as an additional control will help to alleviate this problem. If serial correlation of the error term is caused by serially correlated technology shocks, the coefficient on the capital stock measure will be biased upward but there should be no direct effect on the other coefficient's included in the estimation. Further, serial correlation of the error term and therefore the upward bias on the capital stock coefficient will likely bias the coefficients on the other variables downward.

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Figure 1: Distribution of θ_l^{75} across counties

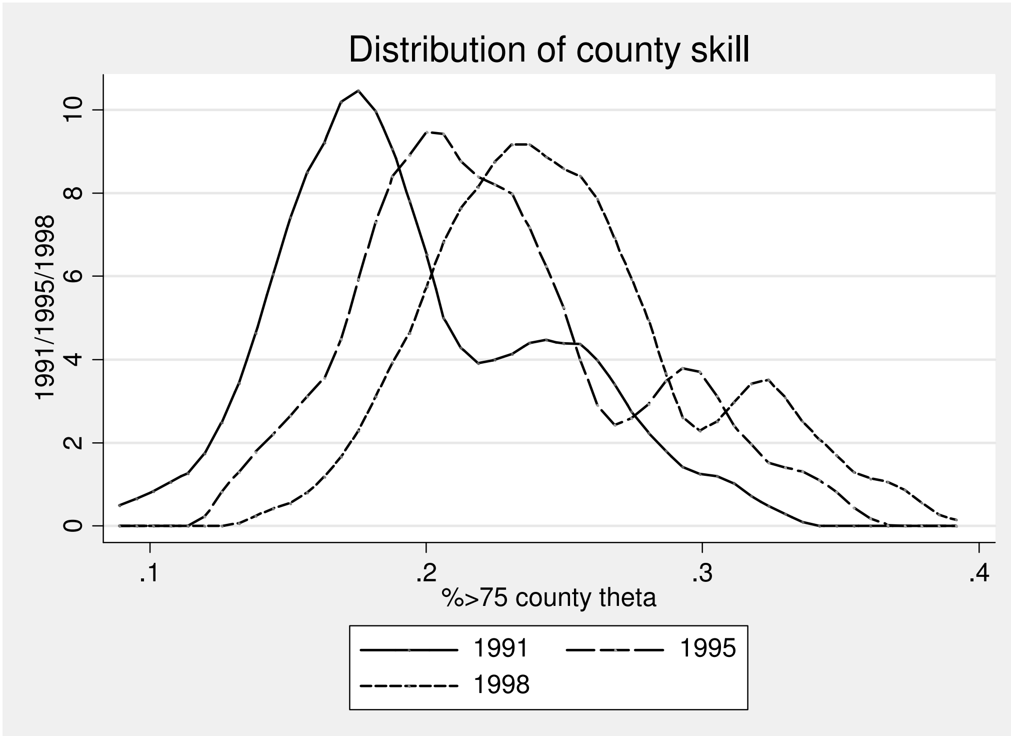

Figure 2: County level skill, 1991-1992

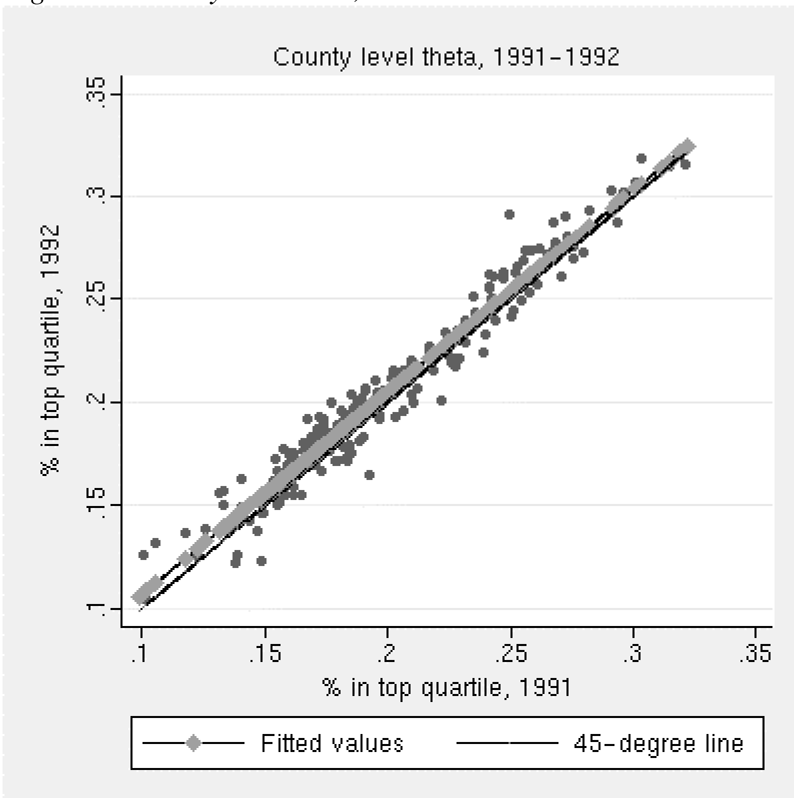

Figure 3: County level skill, 1991-1998

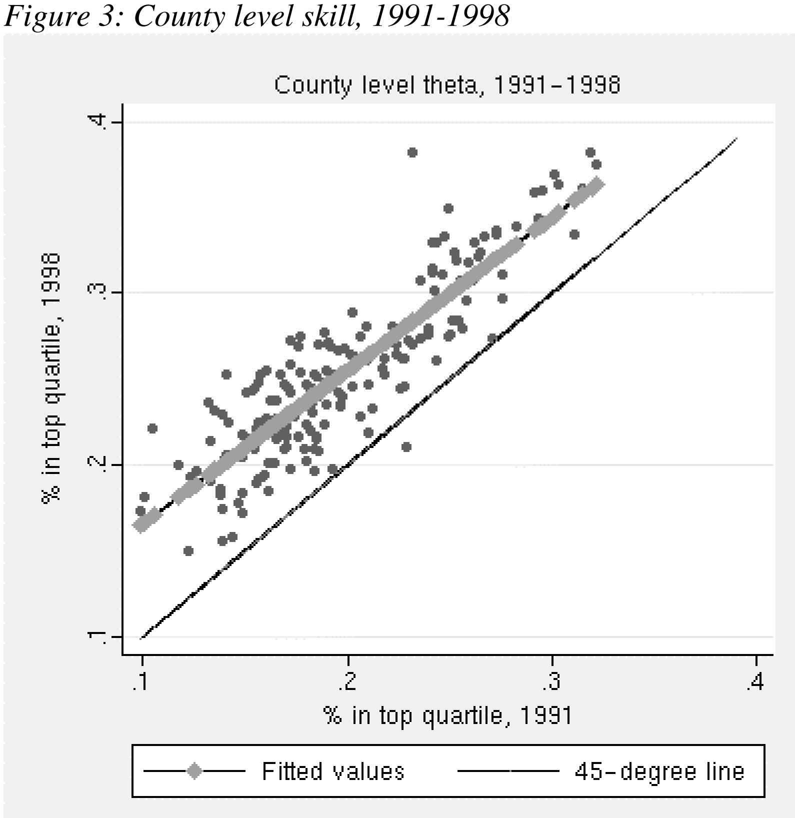

Table 1: Results from Wage Regression

	Log wage	Worker effect	Firm effect	XBeta	Residual
Log wage	1	0.5643	0.4958	0.2294	0.4207
Worker effect		1	0.0655	-0.4740	0.0000
Firm effect			1	0.0355	0.0000
XBeta				1	0.0000
Residual					1

Table 2: Summary Statistics

	Data sample	Number of obs.	Mean	Standard Deviation
Computer Inv. /Machinery Inv.	1992 ASM X UI Wage	6833	0.1110	0.2272
Computer Inv. /Machinery Inv. (weighted)	1992 ASM X UI Wage	6833	0.1114	0.1844
1991 estimated firm effect, ψ	UI Wage	916,896	-0.0138	0.7579
1991 firm skill, $\theta_j^{>75}$	UI Wage	916,896	0.2268	0.2943
1991 county skill, $\theta_l^{>75}$	UI Wage	184	0.1957	0.0476
1991 county skill, $\theta_l^{>75}$ (matched CI/MI sample)	UI Wage X 1992 ASM	6833	0.2471	0.0407
1991 county skill, $\theta_l^{>75}$ (weighted, matched CI/MI sample)	UI Wage X 1992 ASM	6833	0.2467	0.0436

Table 3: Results

Computer Investment/Machinery Investment

	(1)	(2)	(3)	(4)	(5)	(6)
1991 county skill, $\theta_l^{>75}$	0.682*** (0.084)	0.343*** (0.109)	0.099 (0.114)	0.228** (0.089)	0.244*** (0.091)	0.204** (0.086)
1991 estimated firm effect, ψ	-0.059*** (0.015)	-0.038** (0.015)	-0.018 (0.012)	-0.017 (0.012)	-0.013 (0.012)	0.010 (0.014)
1991 firm skill, $\theta_j^{>75}$		0.341*** (0.056)	0.273*** (0.039)	0.243*** (0.040)	0.274*** (0.041)	0.288*** (0.038)
Capital stock per employee						-0.000*** (0.000)
Constant	-0.033* (0.020)	-0.025 (0.023)	-0.012 (0.025)	-0.037 (0.024)	-0.048** (0.024)	-0.029 (0.023)
Observations	6833	6833	6833	6833	6397	6397
R-squared	0.03	0.08	0.15	0.17	0.18	0.19
Ind. controls	no	no	yes	yes	yes	yes
Cty interaction	no	no	no	yes	yes	yes
Capital sample	no	no	no	no	yes	yes
% osd	29.16	14.68	4.25	9.74	10.43	8.73

Robust standard errors based on clustering by county in parentheses. Weighted by ASM sample weight and total value of shipments. County skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Robustness: Nonlinearities

Computer Investment/Machinery Investment

	(1)	(2)	(3)	(4)
1991 county skill, $\theta_l^{>75}$	0.099 (0.114)	0.228** (0.089)	0.253*** (0.092)	0.168** (0.078)
1991 estimated firm effect, ψ	-0.018 (0.012)	-0.017 (0.012)	-0.016 (0.012)	-0.016 (0.012)
1991 firm skill, $\theta_j^{>75}$	0.273*** (0.039)	0.243*** (0.040)	0.242*** (0.043)	0.276*** (0.041)
% workers in high skill ind.				-0.248*** (0.058)
Constant	-0.012 (0.025)	-0.037 (0.024)	-0.041* (0.024)	-0.020 (0.019)
Observations R-squared	6833 0.15	6833 0.17	6833 0.17	6833 0.16
Cty interactions	none	top 1	top 1 & top 5%	none
% osd	4.25	9.74	10.79	7.16

Robust standard errors based on clustering by county in parentheses. Weighted by ASM sample weight and total value of shipments. Two digit industry dummies included. County skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Robustness: Weighting/Firm Size

Computer Investment/Machinery Investment

	(1)	(2)	(3)
1991 county skill, $\theta_l^{>75}$	0.147**	0.008	0.228**
	(0.066)	(0.213)	(0.089)
1991 estimated firm effect, ψ	0.017	0.060**	-0.017
	(0.013)	(0.023)	(0.012)
1991 firm skill, $\theta_j^{>75}$	0.088***	0.113**	0.243***
	(0.026)	(0.046)	(0.040)
Constant	-0.005	0.039	-0.037
	(0.017)	(0.056)	(0.024)
Observations	6833	6833	6833
R-squared	0.06	0.06	0.17
Weight	none	Census	Census*TVS
% osd	6.26	0.34	9.74

Robust standard errors based on clustering by county in parentheses. Two digit industry dummies and interaction terms with high skill county included. County skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Robustness: Alternative Skill Measures

Computer Investment/Machinery Investment

	(1)	(2)	(3)	(4)	(5)
1991 county skill, $\theta_l^{>75}$	0.228** (0.089)				
1991 county skill, $s_l^{>75}$		0.333*** (0.112)			
1991 county skill, θ_l^{mn}			0.119*** (0.034)		
1991 county skill, s_l^{mn}				0.089* (0.048)	
% College Grad					0.230*** (0.058)
Observations R-squared	6833 0.17	6833 0.16	6833 0.16	6833 0.16	6833 0.15
% osd	9.74	12.34	12.22	6.35	12.96

Robust standard errors based on clustering by county in parentheses. Two digit industry dummies, a constant term, and interactions with high skill county are included all the specifications. Firm level skill is included in the first four specifications. Weighted by ASM sample weight and total value of shipments. % college graduates in county calculated from 1990 Census data. County skill measure excludes establishment's contribution in columns 1-4. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Robustness: Alternative Local Labor Market Measure

Computer Investment/Machinery Investment

	(1)	(2)	(3)	(4)
1991 county skill, $\theta_l^{>75}$	0.228** (0.089)		0.229** (0.111)	
1991 msa skill, $\theta_m^{>75}$	-0.017 (0.012)	-0.016 (0.012)	-0.018 (0.013)	-0.018 (0.013)
1991 estimated firm effect, ψ	0.243*** (0.040)	0.247*** (0.039)	0.235*** (0.043)	0.238*** (0.042)
1991 firm skill, $\theta_j^{>75}$		0.206** (0.087)		0.196* (0.111)
Constant	-0.037 (0.024)	-0.033 (0.024)	-0.034 (0.031)	-0.027 (0.033)
Observations R-squared	6833 0.17	6833 0.17	6324 0.17	6324 0.17
Non-metro areas included	yes	yes	no	no
% osd	9.74	7.02	9.78	6.66

Robust standard errors based on clustering by county in parentheses. Weighted by ASM sample weight and total value of shipments. Two digit industry dummies and interaction terms with high skill county included. County and MSA skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: Robustness: Probit

Computer Investment/Machinery Investment

	(1) ols	(2) ols	(3) probit	(4) probit
1991 county skill, $\theta_l^{>75}$	0.390*** (0.093)	0.228** (0.089)	1.773*** (0.468)	1.338*** (0.445)
1991 estimated firm effect, ψ	-0.031** (0.013)	-0.017 (0.012)	-0.029 (0.060)	0.007 (0.059)
1991 firm skill, $\theta_j^{>75}$		0.243*** (0.040)		0.663*** (0.124)
Constant	-0.028 (0.025)	-0.037 (0.024)		
Observations R-squared	6833 0.15	6833 0.17	6814	6814
% osd	16.68	9.74	24.39	18.47

Robust standard errors based on clustering by county in parentheses. Weighted by ASM sample weight and total value of shipments. Two digit industry dummies and interaction terms with high skill county included. County skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Robustness: Machinery Investment per Worker

Panel A: Machinery Investment per Worker, 1992

	(1)	(2)	(3)	(4)
1991 estimated firm effect, ψ	10.898*** (2.954)	11.267*** (3.087)	9.919*** (2.840)	10.269*** (2.949)
1991 county skill, $\theta_l^{>75}$	-5.791 (32.274)	-6.311 (31.954)		
1991 firm skill, $\theta_j^{>75}$	15.094*** (5.556)	15.827** (6.090)		
1991 county skill, $s_l^{>75}$			29.937 (46.036)	29.341 (45.762)
1991 firm skill, $s_j^{>75}$			4.043 (5.831)	4.641 (6.238)
Constant	-3.131 (10.470)	-3.409 (10.588)	-6.704 (12.359)	-6.783 (12.338)
Observations R-squared	56388 0.38	56388 0.38	56388 0.37	56388 0.38
County interactions	none	top 1	none	top 1
% osd	-2.50	-2.72	11.18	10.96

Panel B: Machinery Investment per Worker, 1997

	(1)	(2)	(3)	(4)
1996 estimated firm effect, ψ	21.370*** (3.482)	21.265*** (3.548)	19.911*** (3.831)	19.691*** (3.957)
1996 county skill, $\theta_l^{>75}$	-12.796 (12.746)	-16.912 (12.327)		
1996 firm skill, $\theta_j^{>75}$	19.725*** (5.649)	24.317*** (5.361)		
1996 county skill, $s_l^{>75}$			7.848 (18.132)	5.779 (18.212)
1996 firm skill, $s_j^{>75}$			14.726*** (3.363)	16.690*** (3.548)
Constant	10.524** (4.203)	10.604** (4.172)	5.322 (5.391)	5.395 (5.401)
Observations R-squared	55604 0.26	55604 0.27	55604 0.26	55604 0.26
County interactions	none	top 1	none	top 1
% osd	-4.07	-5.38	2.16	1.59

Robust standard errors based on clustering by county in parentheses. Weighted by total value of shipments. Two digit industry dummies and interaction terms with high skill county included. County skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 10%; ** significant at 5%; *** significant at 1%