How Do Industry Features Influence the Role of Location on Internet Adoption?

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Abstract

We provide a framework and evidence to confront two questions: Does the location of an establishment shape its adoption of different complex Internet applications even when controlling for an industry's features? If location does matter, what features in an industry shape whether Internet adoption follows a pattern consistent with the urban leadership or global village hypotheses? Our findings show that both industry and location play a significant role in explaining the geographic variance in adoption. We also find that industries differ in their sensitivity to location. Information technology–using industries are more sensitive than are information technology–producing industries to the changes in costs and gross benefits affiliated with changes in location size. Moreover, industries with high labor costs and those that are geographically concentrated are more sensitive to changes in gross benefits that occur with increases in location size. Overall, our results provide evidence for an *industrial* digital divide.

Keywords: industrial digital divide, adoption, diffusion

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I. INTRODUCTION

The digital divide at the consumer level has received considerable attention. Poor, uneducated, rural households in the United States are less likely to adopt the Internet than other households. In this paper, we ask whether there also exists an industrial digital divide. In particular, we examine why businesses in different industries differ in their use of advanced Internet technology. An emerging body of work has shown there is considerable variation in business use of Internet technology across locations. It has begun to articulate a framework for understanding this variation [e.g. Kolko, 2000; Charlot and Duranton, 2003; Downes and Greenstein, 2002; Fitoussi, 2003; Forman et al., 2002, 2003a, 2005a]. However, the existing literature has not answered which industry and establishment characteristics drive the industrial digital divide.

In this paper, we take a step toward addressing these issues by showing how industry features and location size affect adoption rates of advanced Internet technology, or *enhancement.*[1] We build on two hypotheses of Internet adoption developed in our earlier work [Forman et al., 2005a] to understand how the use of Internet technology might systematically differ across industries. The global village hypothesis holds that the Internet decreases coordination costs between establishments reducing the importance of distance and leading isolated establishments to adopt first. The urban leadership hypothesis holds that the complementary infrastructure and support services found in cities suggest that urban establishments adopt first.[2] In this paper, we examine how well global village and urban leadership explain variance in enhancement adoption rates across a broad spectrum of industries. Moreover, we examine how industry features shape the geographic pattern of enhancement adoption; in particular, whether the relationships between industry features, location, and Internet adoption are consistent with urban leadership or global village.

[1] Henceforth, *advanced Internet technology* will be used interchangeably with the term *enhancement*. For a more detailed discussion of enhancement, please see our previous work [Forman et al., 2005a].

[2] The global village hypothesis and the urban leadership hypothesis will henceforth be referred to as simply “global village” and “urban leadership” respectively.

We examine detailed IT data at medium and large business establishments in the United States. Approximately two-thirds of the U.S. workforce is employed in the type of establishments studied. Specifically, we analyze Internet adoption at 79,221 establishments that have over 100 employees from 55 industries; this sample comprises almost one-half of U.S. establishments of such size. It also consists of established firms rather than start-ups, which allows us to treat establishment location as exogenous. The data come from a survey updated to the end of 2000 and undertaken by Harte Hanks Market Intelligence (hereafter Harte Hanks), a commercial market research firm. The strength of this data is its coverage of a variety of manufacturing and service industries. Its principal weakness is the absence of reliable estimates about the value of capital stocks. This forces us to use discrete measures of enhancement adoption rather than (the more ideal) dollar value-based units.

We focus on adoption of complex Internet applications that we term enhancement. Enhancement refers to adoption of complex applications requiring technical support and third party servicing. It includes investment in frontier applications such as “e-commerce” or “e-business,” as well as investment in intermediate goods used to support such investments. While both simple and complex Internet applications affect firm performance, complex applications are more likely to be a source of competitive advantage [Porter 2001]. Moreover, there is not much variance in the *adoption* of simple applications among medium and large firms (Forman et al, 2005). There is considerable variance in adoption of complex frontier applications, however. Further, we examine use of enhancement applications that involve communication within the boundaries of the establishment and across establishment boundaries, where we expect variation in the costs and benefits to adopting frontier technology (Forman et al, 2005).

We find that enhancement adoption rates differ between industries due to (1) prior use of other kinds of IT, (2) labor costs, (3) industry growth rates, and (4) geographic concentration. We also find a role for location. As expected, location in major urban areas per se contributes to adoption of advanced IT in most industries, while it deters adoption in a small minority of industries. In addition, we show that the geographic dispersion of an industry partially explains the differences in the average core rates of enhancement adoption between industries.

Last, we identify several industry features that tend to be correlated with adoption patterns consistent with urban leadership, and several more that are associated with global village. In particular, we show that IT-using industries were associated with adoption patterns that were sensitive to both declines in costs and increases in gross benefits as location size changed. In contrast, IT-producing industries were relatively unresponsive to both changes in costs and benefits. Other industry features that proved important were the geographic agglomeration of the industry, labor costs, and industry growth.

This paper's central theme, as with our previous research [Forman et al., 2003a, 2003b, 2005a], provides a different outlook on the digital divide by focusing on the business use of Internet technology. Our results on heterogeneity in adoption strongly suggest there are heterogeneous responses—linked to industrial composition—at regional and national levels in terms of productivity response and economic growth. In turn, because some industries tend to agglomerate around certain geographical locations, the differences in industry features and use of enhancement technology partially explain why regions differ in their use of enhancement technology. By emphasizing the importance of industry differences, our results contrast with some prior findings on the digital divide that emphasize complementarity between Internet use and urban location [NTIA, 2000; Gorman, 2002; Zook, 2000].

II. THEORY AND BACKGROUND

A SIMPLE MODEL OF TECHNOLOGY ADOPTION

We motivate this study from the dramatic variation in Internet adoption rates across regions and industries [e.g., Forman et al., 2003a, 2003b]. Here, however, we focus on analyzing links between use of enhancement and industry characteristics. The simplest model suggests that this regional variation is solely a function of the local composition of industries. In this simple model some locations have high adoption rates because they have a relatively high concentration of "certain type" of industries with tendencies to experiment and adopt frontier Internet applications. Intuitively speaking, our goal is to characterize "type" and analyze its association with observed behavior.

Assuming there are equal costs across locations, no "local spillovers" and exogenous location,[3] the rate of adoption in an industry will be independent of location. Formally,

(1) $r_k = g(x_k)$,

where x_k are nongeographic factors about an industry k that shape adoption rates and r_k is the average rate of enhancement adoption by industry k. In this model, the location of establishments in an industry does not affect adoption rates.

This is a simple "rank" model of technology adoption [Karshenas and Stoneman, 1993], where firms make discrete choices about adoption arising from different rankings of the costs and benefits affiliated with the new technology. Differences between decision makers, here presented as x, explain their different rankings of the technology. At the micro-decision level these also are known as *probit models* [David, 1969].

GLOBAL VILLAGE AND URBAN LEADERSHIP

The alternative to Equation (1) specifies a role for features of the location, that is,

[3] A "local spillover" is a situation in which the number of local firms in an industry affects the adoption rate of other firms in the industry. For example, such spillovers will be positive if large local firms support a third-party market, thereby helping all firms in the neighborhood adopt. Spillovers can also be negative, such as when large firms use all the resources and bid up prices for third-party services. The exogenous location assumption means that most medium to large establishments chose their locations before the Internet became anticipated or available.

(2) $r_k = g(x_k, z_k)$,

where z_k is the locational composition of industry k. Our previous research suggests that we are likely to reject the specification in Equation (1) for a specification like Equation (2). However, this previous research did not employ x_k in any form. Hence, one of the novel contributions of the current research is to understand how much, if any, of regional adoption rates can be attributed to industrial characteristics.

The urban leadership hypothesis predicts that adoption of the Internet will be less common in rural areas than in urban areas, all other things being equal. More formally, we define the prediction of urban leadership as

$$r_{k,\, large} > r_{k,\, rural}\,,$$

where we fix the same industry, but change location. We define $r_{k,\, large} = g(x_k, LG_k(h), RUR_k(l))$ and $r_{k,\, rural} = g(x_k, LG_k(l), RUR_k(h))$, where $LG_k(h)$ means a relatively high percentage of establishments in the industry are in large metropolitan statistical areas (MSAs),[4] and $LG_k(l)$ means a relatively low percentage are in large MSAs. Similarly, $RUR_k(h)$ and $RUR_k(l)$ respectively mean there are relatively high and low percentages of establishments in the industry in rural areas. Thus, $r_{k,\, large}$ has relatively more establishments in large MSAs and relatively few in rural areas compared to $r_{k,\, rural}$.[5] In other words, urban leadership predicts:

Hypothesis 1: An industry's adoption rate increases when a higher fraction of its establishments are located in major urban areas.

There are multiple potential explanations for urban leadership, such as (1) availability of complementary information technology infrastructure, (2) labor

[4] From this point forward, MSAs with populations greater than 1 million will be referred to as *large MSAs*, those with between 250,000 and 999,999 will be *medium MSAs,* those with less than 250,000 will be *small MSAs*, and non-MSA areas will be called *rural*.

[5] Note the implicit correlation between LG_k and RUR_k. The correlation is not perfect. Therefore, using both measurements allows for two different definitions of the relevant margin for urban leadership: being in a large city and (not) being in a rural area. We present separate results for each definition.

market thickness for complementary services or specialized skills, and (3) knowledge spillovers.[6] One other explanation emphasizes that the types of firms found in urban areas are not random. That is, historically IT-friendly establishments may have sorted into areas where costs have previously been low for precursors to Internet technology. It is not our goal to tease out the relative importance of these explanations. Rather, we aggregate them around their common prediction: Adoption increases as location size increases. Because this is the dominant prediction of the existing literature, we treat it as the null, and give it a strong inequality.

In contrast, the global village hypothesis predicts

Hypothesis 2: An industry's adoption rate decreases when a higher fraction of its establishments are located in major urban areas.

Therefore, we define the prediction of global village in the opposite direction, namely,

$$r_{k,\ large} \leq r_{k,\ rural}\ .$$

The global village hypothesis depends on three observations for contrasting predictions. First, while all business establishments benefit from an increase in capabilities, establishments in rural or small urban areas derive the most benefit from overcoming diseconomies of small local size. For example, use of Internet technology may act as a substitute for face-to-face communications.[7] Second, establishments in rural areas lack substitute data communication technologies for lowering communication costs, such as fixed private lines. Third, advanced tools

[6] These are closely related to the three major reasons given for industrial agglomeration [e.g., Marshall, 1920; Krugman, 1991].

[7] Other authors [e.g., Gaspar and Glaeser, 1998] have argued that improvements in IT may increase the demand for face-to-face communication. In other words, they argue that IT and face-to-face communication may be complements. The implication of this hypothesis is that commercial establishments relocate to urban areas in reaction to technical change in IT. However, in our data we observe short-run reactions by commercial establishments to the Internet, before they had the opportunity to relocate. As a result, we do not identify complementary relationships.

such as groupware, knowledge management, Web meetings, and others also may effectively facilitate collaboration over distances.[8]

We observe the short run reaction by industries to the introduction of enhancement. For the majority of establishments in most industries, we expect adoption of Internet technology to require substantial adaptation to meet the idiosyncratic needs of organizations. To perform these adaptations, industries will often rely on the complementary resources that are most prevalent in cities. Thus, consistent with the geographic pattern of adoption for prior innovations, we expect adoption of enhancement to most frequently conform to urban leadership. To further sharpen our predictions, we will consider two types of enhancement technologies for which we anticipate differences in the contribution of global village to shaping adoption behavior. We define our measures of Internet investment in detail below.

INVESTMENT MEASURES AND PREDICTIONS OF GLOBAL VILLAGE AND URBAN LEADERSHIP

Enhancement is our measure of investment in complex Internet applications that are linked to computing facilities, which are often known as "e-commerce" or "e-business." Establishments in our data use complex Internet applications for a variety of purposes, so we forgo measures that would examine investment in a particular application such as e-commerce. Instead, to measure enhancement we look for indications that an establishment has made investments that involved multiple frontier technologies. Most often, these technologies involved inter-establishment communication and/or substantial changes to business processes. [9] We will consider all enhancement applications

[8] Kontzer [2003] provides an overview of collaboration tools and examples of how they reduce the costs of remotely located employees.

[9] An establishment can adopt any of the following enhancement applications: (1) the establishment uses two or more languages commonly used for Web applications, such as Active-X, Java, CGI, Perl, VB Script, or XML; (2) the establishment has over five Internet developers; (3) the establishment has two or more e-business applications, such as customer service, education, extranet, publications, purchasing, or technical support; (4) the establishment reports LAN software that performs one of several functions: e-commerce, Enterprise Resource Planning (ERP), Web development, or Web server; (5) the establishment has an Internet server that is a UNIX workstation or server, mainframe, or minicomputer, or has five or more PC servers, or has

as a group, and then we separate cross-establishment and within-establishment Internet enhancement technologies.

Cross-establishment Internet technologies represent Internet investments that involve communication among establishments within the value chain (e.g., an extranet) or between an establishment and its end consumers. Hereafter, cross-establishment Internet technologies will be termed *CEI*. Within-establishment investments involve use of the Internet's TCP/IP protocols for communication that remains within the boundaries of the establishment. Hereafter, within-establishment Internet technologies will be termed *WEI*. Examples include intranet applications that enable web access to information traditionally stored in business applications software such as inventory or accounting data and applications that have other functionality involving integration with back-end databases (e.g. web access to a data warehouse).[10]

Global village predicts that geographically isolated establishments will have higher gross benefits from communicating with external suppliers and customers. Because CEI investments represent investment in Internet technologies that involve communication across establishments while WEI investments involve communications that are confined within the establishment, we expect gross benefits will vary by location for CEI but will vary negligibly for WEI. As a result, changes in location size and density will primarily influence costs (and not benefits) for WEI. On the other hand, such changes will influence both costs and benefits of CEI adoption. This suggests that any results supporting urban leadership will be stronger for WEI.

Hypothesis 3: As location size increases, the net benefits of adopting WEI will rise faster than those for adopting CEI enhancement.

Internet storage greater than twenty gigabytes; (6) the establishment answers three or more questions related to Internet server software, Internet/Web software, or intranet applications. For a more precise description of some exceptional cases, see the appendix to Forman et al. [2002]. For a similar set of concepts in the context of a study of diffusion of E-Business in the UK, see Battisti, Canepa and Stoneman [2004].

[10] WEI may indirectly facilitate communications beyond the boundaries of the establishment by, for example, enabling electronic integration of supply chains. Our research design enables us to measure this secondary effect by identifying the associated CEI software investment.

This suggests that – controlling for other factors – global village will be especially strong for CEI and urban leadership will be especially strong for WEI enhancement.[11]

The key question in understanding enhancement adoption concerns the difference between $r_{k, large}$ and $r_{k, rural}$ in each industry. One of the novelties of this paper is that we study the relationship between that difference and the features of industries, x_k. In the next section, we detail our method for answering two additional questions: (1) In which industries is the geographic variance in adoption explained by global village and in which industries is it best explained by urban leadership?; (2) Which industry characteristics x_k explain whether urban leadership or global village is most consistent with the data?

III. ECONOMETRIC METHOD

We observe only discrete choices: whether or not the establishment chooses enhancement. We will define these endogenous variables more precisely now.

HOW INDUSTRY AND LOCATION CHARACTERISTICS AFFECT THE RETURNS TO ADOPTION

We begin by examining whether the industry adoption rate for establishments in a specific location can be entirely explained by cross-industry characteristics, or whether local factors have a role in explaining enhancement adoption. To do this, we estimate the industry adoption equation:

$$r_k = \alpha x_k + \beta z_k + \varepsilon_k , \quad (3)$$

where the endogenous variable is $r_k = \frac{\sum_{i \in C_k} y_{ik}}{N_k}$, where $y_{ik} = 1$ if an establishment i in industry k adopts an enhancement application. This variable can be measured in one of three ways—by looking at (1) all enhancement adoption, (2) WEI

[11] As with the other hypotheses in this study, this is a prediction about differences between CEI and WEI adoption at the level of the industry. In other work we have examined the parallel at the level of the establishment. See Forman, et al (2005a).

adoption only, or (3) CEI adoption only. We compute such a rate for all establishments from that industry, here represented as the set, C_k. If we assume that the ε_k are distributed i.i.d. normal across industries, we can recover these parameters using OLS regression. The variables z_k denote the fraction of establishments from industry k in rural areas and small, medium, and large MSAs.

The variables x_k denote industry characteristics unrelated to location size, such as intensity of IT use, whether the industry is an IT producer, labor costs, industry growth rates, and geographic concentration., Our goal is to examine the null hypothesis $\beta = 0$ as well as to examine how industry characteristics x_k affect the cross-industry rate of enhancement adoption. Since we observe short run reactions to advanced Internet technology, we expect that Internet adoption will be increasing in an industry's involvement with other IT, either as a user or producer. Such industries should be lead users of enhancement applications because these industries may have higher benefits (many potential uses) or lower costs (greater experience) from adopting enhancement. We include other industry characteristics as controls. We note that because our measurement framework relies on cross-industry differences in adoption propensity, our vector x_k may also be proxying for cross-industry differences correlated with IT use.[12]

Hypothesis 4: The rate of industry Internet adoption will be positive correlated with intensity of IT use and whether the industry is an IT producer.

In Table 1, we show the results of these regressions.

EXPLORING HOW INDUSTRY CHARACTERISTICS AFFECT THE MARGINAL RETURNS TO LOCATION

As we will show below, we find that location does matter. Since $\beta \neq 0$, we next try to learn about the sources of the variance by asking: (1) In which industries is the geographic variance in adoption explained by global village and

[12] Careful identification of the role of prior IT use on adoption behavior requires variation in IT use within an industry. See Bresnahan and Greenstein (1996) and Forman (2005) for examples.

in which industries is it best explained by urban leadership? (2) Which industry characteristics x_k explain whether urban leadership or global village is most consistent with the data? And (3) are these characteristics consistent with global village being more important than urban leadership in "lead user" industries.

To do this, we first estimate probit adoption equations for establishments in each industry. For example, for industry *k* we assume that the value from adopting an enhancement application to establishment *i* is:

$$y_i = \phi s_{ik} + \lambda w_i + \eta_i \, , \qquad (4)$$

where y_i is latent, and we only observe adoption as a discrete outcome. In this specification s_{ik} denotes dummy variables indicating the type of location inhabited by establishment *i* (small, medium, or large MSAs—rural area is the base), while w_i denotes individual establishment characteristics of establishment i (e.g., establishment size and dummies indicating single- or multi-establishment firm).

We use this model for two purposes. First, we estimate ϕ for each industry, then normalize the results by calculating the marginal effects for each industry, and characterize this distribution. These results (shown in Table 2) represent advancement over our prior work [Forman et al., 2005a], where we presented the average effects of global village and urban leadership, but did not show whether the salience of these hypotheses varied across industries.

As with our prior work, this study measures short run responses to the introduction of advanced Internet technology. Our expectation is that availability of complementary resources will be important to the adoption decisions of establishments in the vast majority of industries. Thus, we expect most industries will display an adoption pattern that is consistent with urban leadership. This expectation is consistent with most prior research on the geographic pattern of diffusion of new IT.

Hypothesis 5: Most industries will display a geographic pattern of adoption consistent with urban leadership.

Our second purpose is to analyze how industry features x_k shape cross-industry variance in the marginal effect of location for each industry, here represented as ϕ_k'. To do this we assume that marginal effects can be written as

$$\phi_k' = \theta x_k + \nu_k \,, \tag{5}$$

where x_k again describes industry characteristics and ν_k is an independently distributed, potentially heteroskedastic error term. We use our first-stage estimates $\hat{\phi}_k'$ in this equation, where $\hat{\phi}_k' = \phi_k + \omega_k$, so our estimation equation is

$$\hat{\phi}_k' = \theta x_k + \nu_k + \omega_k \,. \tag{6}$$

We estimate this equation using OLS and we adjust standard errors for heteroskedasticity and measurement error in the error term $\nu_k + \omega_k$ using White robust standard errors. Since the measurement error is in the dependent variable, the coefficient estimates will be consistent.

This method – i.e., using the coefficients (or marginal effects) of one set of regressions as a dependent variable in another set of regressions – is commonly used in econometric modeling. For example, Nevo (2001) uses brand preference parameters to identify the relationship between brand characteristics and brand preferences. Rossi and Allenby (1993) use individual-specific parameters as dependent variables in testing the relationship between demographics and purchase behavior. Pesaran and Smith (1995) describe some of the econometric details.

We also weight observations by the number of establishments in the industry. The weighting properly accounts for the fact that we model the establishment-level decision. To ensure our results are robust to other specifications, we also run median (quantile) regressions and unweighted OLS regressions. The median regressions ensure that the results of our preferred specification are not caused by a small number of outlying industries. The unweighted regressions ensure that the results are not driven by the largest industries.

In the next subsection we address our third question about which industry characteristics are most likely to be associated with urban leadership and global village. This discussion is necessarily conjectural since the results of cross-industry regressions must be interpreted carefully. Changes in the variables x_k may reflect the influence of changing industry characteristics that are associated with x_k. As a result, our results should be considered exploratory, and await confirmation by other authors.

LEAD USERS, URBAN LEADERSHIP, and GLOBAL VILLAGE

This study will examine business reaction to the availability of the Internet. It is necessarily a short-run reaction, so we expect observed differences between industries to be most associated with industry characteristics that predict early adoption and inclination to experiment with new technology.

IT-PRODUCING: The benefits from geographic dispersion may or may not be greater for IT producing industries, since IT output involves both locally oriented services and internationally traded durable goods. Hence, we have no expectation for the relationship between *IT-PRODUCING* and global village. On the other hand, there is considerable evidence that firms in IT-producing industries are likely on average to have more experience using advanced IT such as the Internet. Moreover, they are more likely to have internal capabilities such as in-house development teams that would reduce their reliance on the complementary external resources found in cities. As a result, we expect such firms to be less sensitive to urban leadership.[13]

Conjecture 1: IT-producing industries will be less likely to be associated with adoption patterns consistent with urban leadership.

IT-INTENSITY: Like firms in IT-producing industries, we expect firms in industries that are heavy users of IT to have internal capabilities that lower the costs of operating outside of cities. Thus, we expect such industries to be associated with a lower likelihood of urban leadership. Because these industries are heavy users of IT, we expect that they may also be more likely than other industries to use Internet technology shortly after its introduction to reduce the

[13] For further exploration of this hypothesis, see Forman et al. (2005b).

costs associated with distance. So we do expect IT-Intensity to predict a tendency to employ the Internet as predicted by global village.

Conjecture 2a: IT-intensive industries will be less likely to be associated with adoption patterns consistent with urban leadership.

Conjecture 2b: IT-intensive industries will be associated with adoption patterns consistent with global village.

LABOR COSTS: Our measure of labor costs is a proxy for an industry's labor costs per unit of output. A long-standing open question in the literature is whether labor-intensive industries employ IT for greater gains than other types of industries. Industries with persistently high labor costs may value enhancement applications that allow the industry to relocate to lower cost locations. As a result, these industries may display adoption patterns that are consistent with global village. We have no prior expectations for how labor costs may influence urban leadership.

Conjecture 3: Industries with high labor costs will be associated with adoption patterns consistent with global village.

GEOGRAPHIC CONCENTRATION: We also measure the geographic concentration of an industry. One common explanation for agglomeration of industries has to do with intense needs to communicate with each other or suppliers, so we conjecture that clustered industries may have a high demand for the external communications capabilities of Internet technology. Isolated establishments from these types of industries will have especially high demands for CEI to coordinate with other establishments in the same industry. They will also have especially high demands to coordinate with partners of other firms in the same industry, where the partners have co-located near the majority of firms. Thus, we expect geographic concentration to be associated with global village.

Conjecture 4: Geographically concentrated industries will be associated with adoption patterns consistent with global village.

IV. DATA

The data we use for this study come from the Harte Hanks Market Intelligence CI Technology database (hereafter CI database).[14] The CI database contains establishment-level data on (1) establishment characteristics, such as number of employees, industry and location; (2) use of technology hardware and software, such as computers, networking equipment, printers and other office equipment; and (3) use of Internet applications and other networking services.

Our sample from the CI database contains all commercial establishments with over 100 employees, 115,671 establishments in all; [15] and Harte Hanks provides one observation per establishment. As with our earlier work, we employ 86,879 clean observations with complete data generated between June 1998 and December 2000. Because we were unable to obtain data on some geographic areas and industry features for some industries, we focus our analysis on 79,221 observations from 55 industries.[16]

IDENTIFYING INDUSTRY CHARACTERISTICS

We compute several proxies for industry characteristics from publicly available data sources.[17] Unless otherwise noted, all calculations are made at the three-digit NAICS level.

IT-PRODUCING and *PCTICT* are measures of the importance of IT in an industry's inputs and outputs. *IT-PRODUCING* is a dummy variable that indicates whether an industry is involved in the production of IT. We follow the classification developed by the Department of Commerce as described by Cooke [2003], which has been used by prior authors [e.g. Daveri and Moscotto, 2002; Nordhaus, 2002]. *PCTICT* is total industry nominal spending on IT hardware and

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[14] This section provides an overview of our methodology. For a more detailed discussion, see Forman et al. [2003c]. For a related discussion in the UK, see Battisti et al. [2004].

[15] Previous studies [Charles, Ivis, and Leduc, 2002; U.S. Bureau of the Census, 2002] have shown that Internet participation varies with business size and that very small establishments rarely make Internet investments for enhancement. Thus, our sampling methodology enables us to track the relevant margin in investments for enhancement.

[16] Of these two criteria, the more binding is the constraint on complete features of industries. We tried to use information that was widely available, but some essential information, such as IT-intensity is not available for all industries.

[17] Definitions for enhancement are provided at the end of section II.

software divided by total nominal spending on equipment and structures. These data were calculated using the 1997 capital flow tables computed by the U.S. Bureau of Economic Analysis. Therefore:

LOW-LABOR-BILL is a proxy for industry labor costs per unit of output. It is equal to total 1997 nominal industry sales divided by total nominal industry payroll. Sales and payroll information are from the 1997 Economic Census. *GEO-CONCENTRATION* is a measure of the geographic concentration of an industry. It is calculated using a locational gini coefficient. To define the gini coefficient, suppose that there are M locations indexed by j. Let I_j denote location j's share of industry employment, and let T_j denote its share of total employment. The locational coefficient for location i is then defined as $LQ(j)=I_j/T_j$. The locational coefficient provides a measure of the concentration of an industry in location j. Resorting the M locations on the basis of decreasing values of the LQ, we define *GEO-CONCENTRATION* as

$$GEO-CONCENTRATION \equiv 1-\sum_{j=1}^{M} T_j \left(I_j + 2\sum_{l=j+1}^{M} I_l \right).$$

Gini coefficients take on values between 0 and 1, where 1 denotes extreme concentration of economic activity and zero denotes equal specialization across locations.[18]

We also include two additional industry controls. *MANUFACTURING* is a dummy that indicates whether the industry is involved in manufacturing activity.[19] The manufacturing dummy will control for manufacturing-specific production features. This dummy does not have a clear interpretation about whether the Internet largely altered input processes or output markets. On the one hand, manufacturing processes differ dramatically from service industries in the ways they employ IT to monitor material flows and input processes. In addition, most of the included establishments produce for national or international output markets while many of the omitted ones produce for predominately local markets, so the

[18] For further information on locational gini coefficients and their use as measures of economic concentration, see Holmes and Stevens [Forthcoming].
[19] Because of the similarity in the production processes, we include construction and mining with manufacturing industries.

variable also measures differences in the relationship between IT investment and location across industries that produce for local and national markets.[20] *EMPGROW* captures the rate of growth in industry employment between 1997 and 2000. For this variable, we use Census data from the 1997 Economic Census and the 2000 Statistics of U.S. Businesses.[21]

V. RESULTS

WHICH INDUSTRY CHARACTERISTICS INFLUENCE THE RETURNS TO ADOPTING ENHANCEMENT?

In Table 1, we show how industry characteristics and geographic location influence the rate with which industries adopted enhancement. Columns 1 through 3 show our baseline OLS estimates of Equation (3). To control for cross-industry differences in the number of establishments in the CI database, we weight each observation by the number of establishments in the industry. There is considerable variation in the enhancement adoption rates across industries. Because we were concerned that outliers could be driving our results, in Columns 4 through 6 we present the results of median regressions.[22] Moreover, for comparison purposes, in Columns 7 through 9 we present the results of unweighted OLS regressions. For each set of estimates, we present the results for the percentage of establishments within an industry adopting enhancement overall, as well as the percentage adopting WEI and CEI, specifically. Because our WEI and CEI measures allow for cleaner predictions about how location affects the adoption of enhancement, we focus on these results and include the

[20] We also explored other measures of output market characteristics, such as concentration in output markets, such as C4 and C8 indices from the 1997 Economic Census. However, these were not available for eight industries and largely did not predict adoption in the subset where they were available. So these were dropped from the final estimates.
[21] Data prior to 1997 are only available based on the old Standard Industrial Classification (SIC), and are not available on a NAICS basis. Thus, we were unable to use this earlier data for our study.
[22] In median regression, the estimator minimizes the absolute deviations from the median rather than the squared deviations from mean, as in OLS.

overall measure primarily for comparison purposes. We include the percentage of industry establishments in small, medium, and large MSAs; the omitted category contains establishments in rural areas With the exception of *LOW-LABOR-BILL*, all variables are scaled between 0 and 1. Thus, we will focus on marginal effect of a 0 to 1 change in the right hand side variables.

The results of Table 1 strongly reject the null that location has no effect on enhancement adoption. A regional effect is significant in six of the nine columns. Moreover, a regional effect has the strongest marginal effect (in absolute value) in all but one of the specifications. Adoption generally increases as location size increases—the coefficients for large MSAs are positive. The coefficient for medium MSAs is significantly positive in column 2. It is never significantly negative. This result is consistent with hypothesis 1. As we expected, we see less evidence of hypothesis 2 when examining adoption of complex Internet technology separately. By comparing Columns 2 and 3, we see that increases in the fraction of establishments in large areas seem to have a weaker effect on CEI than on WEI. This is consistent with hypothesis 3. Moreover, increases in locational concentration also have a weaker effect on CEI adoption than on WEI adoption: the coefficient is both smaller and insignificant.

Overall, these differences are consistent with both global village and urban leadership. The effects of increasing location size on the adoption of CEI will reflect decreasing gross benefits as well as decreasing costs. In contrast, the effects of increasing location size on the adoption of WEI will affect only the costs of adoption. As a result, adoption of CEI increases more slowly as location size increases than adoption of WEI does. The results of Columns 5 and 8 have the same message as Column 2.

We now turn to the industry variables. The evidence is weakly consistent with the hypothesis that the rate of Internet adoption will be greater for industries that use other forms of IT in its inputs and outputs (Hypothesis 4). *PCTICT* has a significantly positive effect on the adoption of overall enhancement and WEI in median and unweighted regression, but no significant effect in the weighted regression. *IT-PRODUCING* is usually associated with a higher rate of Internet adoption, but is usually not statistically significant. Column 2 shows that an industry's labor bill and dispersion each have strong positive effects on adoption of WEI. The coefficient on *GEO-CONCENTRATION* is particularly large; an increase in the locational gini coefficient from its minimum to its maximum (0.176 to 0.936) increases the adoption rate by 20.5%.

The factors affecting CEI adoption are more sensitive to the specification used. Increases in the percentage of establishments in large MSAs have a positive and significant effect on CEI adoption under both median and unweighted regression. *GEO-CONCENTRATION* also has a positive and significant effect on CEI adoption when using median regression, however the coefficient estimate remains smaller than that on WEI adoption.

LOW-LABOR-BILL has a significantly positive effect on WEI adoption, suggesting advanced Internet technology is used first in industries with low labor costs.

WHICH INDUSTRIES DISPLAY ADOPTION CONSISTENT WITH GLOBAL VILLAGE AND WHICH ARE CONSISTENT WITH URBAN LEADERSHIP?

In Table 2, we summarize the distribution of marginal effects from the large, medium, and small MSA dummies. These marginal effects are calculated as the change in adoption probability as the result of a 0/1 change in the corresponding location dummy. Looking from top to bottom, the findings show that there are more industries consistent with urban leadership than with global village (Hypothesis 5). To develop this insight we first begin with a comparison across rows.

Across all types of locations and WEI and CEI investment, the percentage of positive marginal effects ranges from 65.5% to 70.9%. For large MSAs, fourteen industries (of fifty-five) display significantly positive marginal effects for WEI investment, while twelve industries display significantly positive marginal effects for CEI. In contrast, there are no industries with significantly negative marginal effects for WEI investment and five for CEI.

The distributions for both WEI and CEI are skewed: The mean is larger than the median in all cases. Although the mean for CEI investment is higher than that for WEI investment for all size classes, the 25th percentile is lower. Overall, these results suggest that although CEI adoption decreases as location size increases for some industries, these tend to be the minority. For most industries, CEI adoption either increases or is unchanging as location size increases, which provides support for urban leadership on balance. As expected, there is no evidence that WEI adoption decreases as location size increases.

To illustrate the meaning of the marginal effects for individual industries, we consider the bottom ten marginal effects for large MSAs in CEI investment, where the impact of global village is particularly strong.[23] As might be expected from global village, the industries ranked as the bottom ten include (1) those that are mainly located in geographically isolated areas (Oil and Gas Extraction; Textile Product Mills; Amusement, Gambling, and Recreation), (2) those that are coordination-intensive (Truck Transportation, Accommodation, Hospitals), or (3) those that operate in a large variety of locations (Hospitals; Accommodation; Heavy Construction).[24] The ranking for the top ten industries for WEI investment—for which urban leadership is unusually strong—are very different. This list includes industries that are traditionally geographically agglomerated (Management of Companies and Enterprises; Publishing Industries; Support Activities for Mining; Transportation Equipment Manufacturing; Printing and Related Activities; Computer and Electronic Product Manufacturing).[25]

WHAT INDUSTRY FEATURES EXPLAIN DIFFERENCES IN THE SENSITIVITY OF ADOPTION TO INDUSTRY LOCATION?

In Tables 3 through 5, we show estimates of Equation (6), which analyzes which industry features explain differences in an industry's sensitivity to location. For robustness we examine both the difference between a large MSA and a rural

[23] These results are not included in any table, as they are quite lengthy, but are available from the author upon request.

[24] Other industries in the bottom ten include Insurance Carriers -12.8%; Nonstore retailers -12.1%; Primary Metal Manufacturing -6.6% and Credit Intermediation -3.4%.

[25] Other industries in the top ten for WEI investment include Credit Intermediation and related activities 7.1%; Leather and Allied Product Manufacturing 4.0%; Oil and Gas Extraction 3.1%; and Chemical Manufacturing 2.2%.

area (Table 3), as well as the difference between large MSAs and small MSAs (Table 4). Because we consider this an exploratory analysis of how industry characteristics shape the geographic pattern of adoption, we discuss both results for which we have made conjectures as well as other results that are statistically or economically significant.

We first examine the results for WEI applications. Positive coefficients in these specifications indicate that increases in the variable increase the rate at which industry adoption increases as location size increases, consistent with urban leadership.

Surprisingly, Column 2 of Table 3 shows that industries that heavily use IT as part of their production process are significantly more likely to adopt WEI technology in larger urban areas. The coefficient estimate on *PCTICT* is a statistically significant at 0.21. *PCTICT* is also significant in the median regression (Column 5); however, it is insignificant (though large) in the unweighted regression (Column 8). These results also hold when one compares the difference between large and small MSA dummies (see Table 4). These results contradict our predictions in Conjecture 2a. These results may reflect the presence of unmeasured industry characteristics correlated with *PCTICT* that lead to a propensity for urban leadership, however we are unable to isolate these using our measurement framework.

While increases in IT inputs increase the rate at which industry adoption increases as location size increases, the reverse is true for IT outputs. Although these effects are statistically insignificant when one examines large MSA dummies, they are much clearer when one examines the difference between large and small MSA dummies. In Table 4, the coefficient for IT-producing is negative and significant in weighted and median regressions, though it is insignificant in unweighted regression. Overall, these results are consistent with Conjecture 1.

We now examine non-IT variables: Increases in LOW-LABOR-BILL decrease the rate at which industry adoption increases as location size increases. This is true whether we use large MSA dummies (Table 3) or the difference between large MSAs and small MSAs as the dependent variable (Table 4), and it also does not depend on whether we use weighted, unweighted, or median regression. Overall, these results show that industries in which labor costs are low (relative to output) will be less sensitive to increases in location size. This suggests that industries with low labor costs may be relatively self-sufficient in IT use as they require less of the complementary resources located in urban areas. The coefficient on *EMPGROW* sometimes has a significant impact on an industry's sensitivity to location in both Tables 3 and 4, although the result is not robust across specifications.

We next examine CEI applications. From Tables 3 and 4, we can see that increases in industry concentration—as measured through *GEO-CONCENTRATION*—increase the importance of global village relative to urban leadership. In other words, very concentrated industries tend not to be characterized by urban leadership.

One difficulty in interpreting the CEI results is that they reflect the impact of changing costs and benefits across location size. To partially control for changes in CEI adoption costs across locations, we re-estimated Equation (6) using $\hat{\phi}'_{CEI} - \hat{\phi}'_{WEI}$, the difference between CEI and WEI coefficients, as the dependent variable. If the change in cost is similar in magnitude for CEI and WEI investment, this regression will provide us with the industry features that supported global village. In other words, in what types of industries did the benefit of overcoming distance shape Internet adoption? This is one method for isolating the factors that determined "lead users" apart from facing difference costs.

In Table 5, we show the results of this regression. Because increases in $\hat{\phi}'_{CEI} - \hat{\phi}'_{WEI}$ mean that global village is less successful in explaining adoption patterns, a positive coefficient suggests that an increase in the industry feature tends to decrease the role of global village in explaining enhancement adoption. If our conjectures are correct, then a statistically significant negative coefficient identifies industry features that correlate with experimental use of the Internet.

The coefficient estimates for *IT-PRODUCING* are positive, suggesting that the derivative of gross benefits with respect to location size is higher for IT-producing industries. In other words, IT-producing industries are less likely to exhibit global village than non-IT-producing industries. In contrast, the estimates for *PCTICT* are negative: global village is likely to be more important for heavy IT-using industries. This is consistent with Conjecture 2b. Thus, this suggests that typical lead users of enhancement may operate with two distinct motives. Whereas IT-using industries tend to support global village, IT-producing ones do not.

The coefficients on *LOW-LABOR-BILL* are positive and significant for all specifications except Column 1, suggesting that highly labor intensive industries are more likely to demonstrate geographic variance consistent with global village. This is consistent with Conjecture 3. This is consistent with the view that industries with higher labor bills have tended to use the Internet to coordinate across distances. It is also consistent with the conjecture that industries with traditionally high labor costs, which establishments have been unable to lower, have tried (or did try after we observed them in 2000) to use enhancement to facilitate relocating activity to rural areas to save on labor costs. The coefficient on *EMPGROW* sometimes has a significant impact on an industry's sensitivity to location, although the result is not robust across specifications.

The coefficient on *GEO-CONCENTRATION* is generally negative across specifications, suggesting that agglomerated industries will be more sensitive to global village than non-agglomerated industries and consistent with conjecture 4. In a standard rank model of adoption, such industries would be labeled the earliest adopters. It is as if the industries with the least geographic dispersion have the highest demand for expanded external communications and, thus, are the first ones to take advantage of the new capability. This result raises intriguing questions about what other industry traits correlate with an industry with especially high agglomeration prior to the diffusion of the Internet.[26]

[26] We also experimented with adding industry exports and foreign direct investment (FDI) to our econometric models, which we conjectured might have been correlated with older "capital intensive" industries, who are both agglomerated and have large exports (e.g., aeronautics). Our

VI CONCLUSION

We have examined some of the causes of the industrial digital divide. Overall, our results show that location significantly increased the likelihood of adoption for some industries investing in WEI and reduced the likelihood for a smaller minority investing in CEI. Thus, we respond to our first question affirmatively: Location of an establishment does shape its adoption of enhancement even when controlling for an industry's features. We further showed that for the majority of industries, the geographic pattern of advanced Internet technology diffusion was similar to that for other advanced IT: most industries displayed a pattern of adoption consistent with urban leadership.

For the last question—which features affect the relative importance of urban leadership and global village—we show that IT-using industries were more sensitive to both declines in costs (consistent with urban leadership) and declines in gross benefits (consistent with global village) as location size changed. In contrast, IT-producing industries were less sensitive to either changes in costs or benefits as location size changed. This suggests that IT-using industries were sensitive to the complementary resources available in large urban areas, but also may have used IT to lower coordination costs associated with distance. Unsurprisingly, however, IT-producing industries were relatively unresponsive to such changes in resources, and were also less likely to use IT to reduce coordination costs associated with distance.

Other industry features that proved important were the geographic agglomeration of the industry, labor costs, and industry growth. Of most importance, we found that geographically concentrated industries were also more likely to invest in CEI.

Our research is part of a larger agenda to alter the conversation about the digital divide within the United States. In contrast to most prior work that has examined early consumer adoption of the Internet, we examined the first

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results are robust to the inclusion of measures of foreign investment. These models suggest that Internet adoption may be complementary with urbanization for exporters. However, this was not sufficient to settle the question. FDI activity tends to be highly skewed between firms within an industry. Because of within-industry variance in exporting/FDI, we would require establishment-level data on these variables to identify their impact on Internet adoption behavior.

response of the U.S. industry to the availability of the commercial Internet. Moreover, our findings also speak to the prevailing literature on the geographic digital divide that emphasizes complementarity between Internet use and urban location [NTIA 2000; Gorman 2002; Zook 2000] Use of enhancement is shaped by an industry's features and the prior geographic distribution of industry. Like many General Purpose Technologies [Bresnahan and Trajtenberg 1995], the availability of the Internet did not result in the same commercial experience for all establishments in all locations. The prior distribution of industry must be considered in addition to the fact that urban and rural establishments have different incentives to adopt the technology. Combined, these factors led to variance in adoption rates across US regions.

Our findings also begin to form the foundation for further serious speculation about how communications improvements brought about by technical change in IT can alter the long run location decisions of firms. These technologies then can engender changes in the comparative economic advantage of regions. Our study is a short-run analysis that holds establishment locations fixed. It is too soon to observe the long-run movement of establishments in reaction to this diffusion; however, in time future research should begin to address these questions. The open question is: Which industries will become more geographically dispersed? Will changes in geographic dispersion bring about changes in labor costs that result in further productivity improvement? Even more speculatively, which locations will gain and which will lose when industries reorganize geographically in this way? These questions and others will be active areas for future research.

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Table 1. What Do IT-Intensive Industries Look Like?

Endogenous Variable (Percentage of Establishments within an Industry Using …)	(1) Overall Enhancement	(2) WEI	(3) CEI	(4) Overall Enhancement	(5) WEI	(6) CEI	(7) Overall Enhancement	(8) WEI	(9) CEI
Method	Weighted	Weighted	Weighted	Median	Median	Median	Unweighted	Unweighted	Unweighted
Percentage in Large MSAs	0.0472	0.1763	0.1150	0.1524	0.3234	0.3559	0.1823	0.1899	0.2857
	(0.0978)	(0.1363)	(0.1580)	(0.0703)*	(0.0991)**	(0.1188)**	(0.0621)**	(0.1200)	(0.1061)**
Percentage in Medium MSAs	-0.00974	0.5291	0.1394	-0.2582	-0.0756	-0.1787	-0.1903	0.0939	-0.2540
	(0.2307)	(0.2670)+	(0.4291)	(0.2071)	(0.2752)	(0.3372)	(0.1999)	(0.2800)	(0.3521)
Percentage in Small MSAs	0.2393	-0.1564	0.4683	0.1261	-0.1099	0.1123	0.1089	-0.0822	0.2341
	(0.2370)	(0.3372)	(0.4077)	(0.2024)	(0.3318)	(0.3359)	(0.2162)	(0.3128)	(0.3562)
IT-PRODUCING	0.0691	0.0557	0.0868	0.0582	0.0233	-0.0161	0.0470	0.0409	0.0365
	(0.0574)	(0.0738)	(0.0831)	(0.0274)*	(0.0342)	(0.0416)	(0.0308)	(0.0355)	(0.0374)
EMPGROW	-0.04319	-0.0505	-0.1059	0.00249	0.0135	-0.0194	-0.00503	-0.0226	-0.0402
	(0.07300)	(0.0894)	(0.1136)	(0.0661)	(0.0700)	(0.1112)	(0.0586)	(0.0873)	(0.0847)
LOW-LABOR-BILL	0.00281	0.00477	0.00467	0.00103	0.00438	7.29E-05	0.00175	0.00323	0.00261
	(0.00220)	(0.00155)**	(0.00349)	(0.00119)	(0.00139)**	(0.00141)	(0.00119)	(0.00148)*	(0.00158)
GEO-CONCENTRATION	0.0329	0.2701	0.0451	0.0409	0.2202	0.1663	0.1090	0.2120	0.1277
	(0.0792)	(0.0799)**	(0.1273)	(0.0521)	(0.0660)**	(0.0806)*	(0.0450)*	(0.0656)**	(0.0778)
PCTICT	0.1491	0.1999	0.0861	0.1083	0.2518	0.1444	0.1068	0.2429	0.0893
	(0.1043)	(0.1425)	(0.1572)	(0.0538)*	(0.0695)**	(0.0905)	(0.0548)+	(0.0699)**	(0.0713)
MANUFACTURING	-0.0494	-0.0587	-0.0492	0.00365	0.0186	0.00674	-0.0206	-0.0107	-0.00151
	(0.0209)*	(0.0251)*	(0.0308)	(0.0191)	(0.0248)	(0.0311)	(0.0168)	(0.0227)	(0.0247)
Constant	0.0654	-0.2077	0.1023	0.0470	-0.2065	0.00517	-0.000200	-0.1406	0.0512
	(0.0793)	(0.1202)+	(0.1325)	(0.0648)	(0.0898)*	(0.1046)	(0.0484)	(0.1207)	(0.1018)
Number of Industries	55	55	55	55	55	55	55	55	55
R^2	0.5	0.74	0.44	0.37	0.43	0.28	0.56	0.61	0.37

* significant with 95% confidence
** significant with 99% confidence
\+ significant with 90% confidence

Table 2. Descriptive Statistics

	Overall Enhancement Adoption Rates	WEI Adoption Rates	CEI Adoption Rates
Percentage of Industry that Adopts	14.8%	14.6%	27.0%
Number of Industries	55	55	55
Large MSA*			
Number of Industries Significantly Positive†	15	14	12
Number of Industries Significantly Negative†	3	0	5
Percentage That Is Positive	63.6%	69.1%	65.5%
Mean Marginal Effect	0.0212	0.0127	0.0285
75th Percentile Marginal Effect	0 .0497	0.0149	0.0680
Median Marginal Effect	0.0127	0.00197	0.0249
25th Percentile Marginal Effect	-0.00589	-7.17e-06	-0.0194
Medium MSA*			
Number of Industries Significantly Positive†	11	8	10
Number of Industries Significantly Negative†	3	1	0
Percentage That Is Positive	67.3%	67.3%	65.5%
Mean Marginal Effect	0.0239	0.0189	0.0421
75th Percentile Marginal Effect	0.0472	0.0205	0.0692
Median Marginal Effect	0.00605	0.00118	0.0285
25th Percentile Marginal Effect	-0.00380	-0.000052	-0.0305
Small MSA*			
Number of Industries Significantly Positive†	6	1	4
Number of Industries Significantly Negative†	1	2	1
Percentage That Is Positive	54.5%	70.9%	67.3%
Mean Marginal Effect	0.0257	0.0347	0.0558
75th Percentile Marginal Effect	0.0438	0.0169	0.0602
Median Marginal Effect	0.00632	0.00175	0.0198
25th Percentile Marginal Effect	-0.0162	-3.44e-06	-0.00867

* Base is non-MSA.

† With at least 90% confidence.

Table 3. What Affects Whether an Industry Is Sensitive to Location? Large MSA Dummies (relative to rural areas)

Endogenous Variable (Percentage of Establishments within an Industry Using …)	(1) Overall Enhancement	(2) WEI	(3) CEI	(4) Overall Enhancement	(5) WEI	(6) CEI	(7) Overall Enhancement	(8) WEI	(9) CEI
Method	Weighted	Weighted	Weighted	Median	Median	Median	Unweighted	Unweighted	Unweighted
IT-PRODUCING	-0.00661	-0.0951	-0.02724	0.0351	-0.00767	0.0591	0.00643	-0.0288	0.0758
	(0.0333)	(0.0611)	(0.0726)	(0.0230)	(0.0104)	(0.0291)*	(0.0320)	(0.0415)	(0.0348)*
EMPGROW	-0.1921	-0.1237	0.2099	-0.1474	-0.0552	0.0126	-0.0964	-0.1064	0.0631
	(0.0635)**	(0.0787)	(0.2265)	(0.0620)*	(0.0237)*	(0.0657)	(0.0459)*	(0.0592)+	(0.1143)
LOW-LABOR-BILL	0.00252	-0.00196	-0.00188	0.00147	-0.000220	0.00340	0.00187	-0.00189	0.00163
	(0.00124)*	(0.000900)*	(0.00435)	(0.00127)	(0.000379)	(0.00111)**	(0.000764)*	(0.000888)*	(0.00191)
GEO-CONCENTRATION	0.00226	0.0562	-0.2413	-0.00484	-0.0116	0.0132	0.00946	0.00334	-0.1043
	(0.0385)	(0.0555)	(0.1010)*	(0.0481)	(0.0152)	(0.0479)	(0.0294)	(0.0372)	(0.0642)
PCTICT	0.0741	0.2138	-0.0941	0.0199	0.0660	-0.0736	0.00338	0.1314	-0.1584
	(0.0700)	(0.1148)+	(0.1562)	(0.0628)	(0.0187)**	(0.0637)	(0.0544)	(0.0811)	(0.1090)
MANUFACTURING	-0.0407	-0.0275	0.0505	-0.00765	0.00539	0.0104	-0.0178	-0.00498	0.0200
	(0.0188)*	(0.0186)	(0.0650)	(0.0224)	(0.00624)	(0.0212)	(0.0111)	(0.0107)	(0.0307)
Constant	0.0197	-0.0140	0.1780	0.0169	0.000384	-0.00700	0.0144	0.00446	0.0829
	(0.0230)	(0.0226)	(0.0738)*	(0.0248)	(0.00771)	(0.0236)	(0.0153)	(0.0167)	(0.0440)+
Number of Industries	55	55	55	55	55	55	55	55	55
R^2	0.45	0.47	0.41	0.14	0.10	0.07	0.18	0.29	0.1

*significant with 95% confidence
**significant with 99% confidence
+significant with 90% confidence

Table 4. What Affects Whether an Industry Is Sensitive to Location?
Differences Between Large MSA and Small MSA Dummies

Endogenous Variable (Percentage of Establishments within an Industry Using …)	(1) Overall Enhance-ment	(2) WEI	(3) CEI	(4) Overall Enhance-ment	(5) WEI	(6) CEI	(7) Overall Enhance-ment	(8) WEI	(9) CEI
Method	Weighted	Weighted	Weighted	Median	Median	Median	Unweighted	Unweighted	Unweighted
IT-PRODUCING	-0.3320	-0.4361	-0.2325	-0.0146	-0.0154	0.0277	-0.0670	-0.1143	-0.00474
	(0.1348)*	(0.1551)**	(0.1149)*	(0.0408)	(0.00269)**	(0.0402)	(0.0360)+	(0.0752)	(0.0498)
EMPGROW	0.3172	0.7673	0.0423	-0.00435	0.00272	-0.1197	-0.1200	0.1066	-0.2013
	(0.2487)	(0.2849)**	(0.2390)	(0.1021)	(0.00731)	(0.0965)	(0.142)	(0.1497)	(0.1917)
LOW-LABOR-BILL	-0.00331	-0.00947	0.00497	0.000781	-0.000510	0.00516	-0.000390	-0.00473	0.00538
	(0.00398)	(0.00478)+	(0.00335)	(0.00193)	(0.000120)**	(0.00149)**	(0.00243)	(0.00331)	(0.00213)*
GEO-CONCENTRATION	-0.0214	-0.2080	-0.3682	0.0572	-0.00292	-0.0974	-0.0383	-0.1136	-0.2418
	(0.1008)	(0.2080)	(0.1618)*	(0.0713)	(0.00499)	(0.0670)	(0.0753)	(0.1083)	(0.1030)*
PCTICT	0.5557	0.8292	0.5394	0.0968	0.0517	-0.0691	0.2227	0.3514	0.0899
	(0.1392)**	(0.2767)**	(0.2008)**	(0.0797)	(0.00521)**	(0.0806)	(0.0703)**	(0.1700)*	(0.1319)
MANUFACTURING	0.1328	0.3095	0.2733	0.00104	0.000535	0.0353	0.0324	0.0850	0.1001
	(0.0519)*	(0.1991)	(0.1369)+	(0.0301)	(0.00210)	(0.0290)	(0.0239)	(0.0762)	(0.0539)+
Constant	-0.1572	-0.2128	-0.1502	-0.0474	-0.00304	0.00476	-0.0383	-0.0478	-0.0113
	(0.0628)*	(0.1602)	(0.1253)	(0.0368)	(0.00248)	(0.0335)	(0.0411)	(0.0710)	(0.0639)
Number of Industries	55	55	55	55	55	55	55	55	55
R^2	0.51	0.44	0.24	0.10	0.03	0.09	0.18	0.13	0.15

* significant with 95% confidence
** significant with 99% confidence
+ significant with 90% confidence

Table 5. What Increases the Benefits from Global Village?
The Difference between the Rates of CEI and WEI

Regional Comparison	(1) Difference between Large MSAs and Rural Areas	(2) Difference between Large MSAs and Rural Areas	(3) Difference between Large MSAs and Rural Areas	(4) Difference between Large and Small MSAs	(5) Difference between Large and Small MSAs	(6) Difference between Large and Small MSAs
Method	Weighted	Median	Unweighted	Weighted	Median	Unweighted
IT-PRODUCING	0.0650	0.0853	0.1046	0.2022	0.0887	0.1096
	(0.0930)	(0.02286)**	(0.0287)**	(0.0865)*	(0.0460)+	(0.0563)+
EMPGROW	0.3460	0.2151	0.1695	-0.753	-0.1320	-0.3079
	(0.2579)	(0.06316)**	(0.1302)	(0.1492)**	(0.0973)	(0.1313)*
LOW-LABOR-BILL	8.40E-05	0.00546	0.00353	0.0141	0.00995	0.0101
	(0.00495)	(0.000753)**	(0.00206)+	(0.00277)**	(0.00136)**	(0.00217)**
GEO-CONCENTRATION	-0.2929	0.0182	-0.1077	-0.1528	-0.1118	-0.1282
	(0.1183)*	(0.0421)	(0.0759)	(0.0956)	(0.0673)	(0.0758)+
PCTICT	-0.3101	-0.2077	-0.2898	-0.3215	-0.2241	-0.2615
	(0.1962)	(0.0509)**	(0.0960)**	(0.2622)	(0.0823)**	(0.1285)*
MANUFACTURING	0.0766	0.0188	0.0250	-0.0588	0.0438	0.0150
	(0.0733)	(0.0181)	(0.0337)	(0.0838)	(0.0272)	(0.0336)
Constant	0.1904	-0.0250	0.0784	0.0903	0.00412	0.0365
	(0.0786)*	(0.0202)	(0.0441)+	(0.0975)	(0.0333)	(0.0466)
Number of Industries .	55	55	55	55	55	55
R^2	0.44	0.13	0.22	0.68	0.22	0.4

* significant with 95% confidence
** significant with 99% confidence
+ significant with 90% confidence