Adoption of the Internet by Commercial Establishments: Urban density, Global Village and Industry Composition

June 2003

Chris Forman, Avi Goldfarb, and Shane Greenstein[*]

Abstract

This study offers hard evidence on the geographic dispersion of electronic commerce to businesses. We test opposing theories on how urban locations influenced the diffusion of Internet technology. Global village theory asserts that Internet technology reduces the importance of distance and reverses the trend to urbanization. Urban density theory predicts that the Internet follows a traditional pattern of diffusion, first to urban areas with complementary technical and knowledge resources. A third theory, industry composition, argues that some of the geographic variation in use is due to the agglomeration of IT-intensive industries.

The paper finds evidence that participation in the Internet is more likely in rural areas than in urban areas once controls for industry are included. Nevertheless, talk about the dissolution of the city is premature. Frontier Internet technologies appear more often at establishments in urban areas, even with industry controls. Major urban areas also contain many establishments from IT-intensive industries, which acts to reinforce the concentration of frontier Internet technologies in large urban areas. However, because IT-intensive industries are numerous and widespread, so too is the use of frontier technology.

---

[*] Respectively at Carnegie Mellon University, University of Toronto and Northwestern University. We thank Tim Bresnahan, Steve Klepper, Roger Noll, Alicia Shems, Manuel Trajtenberg seminar participants at the Center for Economic Studies, and especially Scott Stern for comments. We also thank Harte Hanks Market Intelligence for supplying data. We received funding from the Kellogg School of Management and the GM Strategy Center and seed funding from the National Science Foundation and Bureau of Economic Analysis. All opinions and errors are ours alone.

1. Introduction

While information technology spending had been growing rapidly over 1990 to 1995, the timing and form of the Internet's commercialization caught all but a small number of technical cognoscenti by surprise. After 1995 the vast majority of business establishments were faced with a decision about how to react to the availability of new capabilities.

US business reacted with the largest growth rates in investment in information technology in the history of the United States. Stocks of information technology capital grew at a 20% annual growth rate from the end of 1995 to the end of 2000.[1] By 2000 computer hardware and software stocks had reached 622.2 billion dollars.[2] The majority of this investment was affiliated with enabling business applications. In 2000, for example, business investment in IT goods and services was almost triple the level for personal consumption of similar goods.[3]

The level of these investment flows is immense and so is the variance across locations.[4] Enterprises in some locations have completely adopted the Internet across all facets of economic activity, while other locations are still at the earliest stages of adjusting to digital technology. Two competing theories for explaining this variance have received the most attention. First, "global village" theory predicts that firms in small cities and rural areas adopted the Internet more quickly than urban firms because the marginal returns to use are higher in a remote location or a location lacking economies of density. In contrast,

[1] This includes computer hardware, computer software, communications hardware and instruments. See Price and McKittrick (2002) or Henry and Dalton (2002). The growth rates are even higher if communications equipment and instruments are excluded.
[2] These are constant (1996) dollars. See Henry and Dalton (2002).
[3] For 2000, estimated personal consumption of IT goods and services was $165 billion. For business it was $466 billion. See Henry and Dalton (2002).
[4] For extensive description of this variance, see our previous paper, Forman, Goldfarb and Greenstein (2002).

the "urban density" theory predicts adoption will be most extensive in big cities because they have pooled resources that lower the costs of adopting new technologies.

Despite much speculation about the pattern of diffusion and much policy interest, little empirical research confirms or refutes competing hypotheses. This paper is the first to adjudicate this debate with hard data. Specifically, our study concentrates on a single, major, well defined, and reasonably well recorded development – adoption of business applications of the Internet – to test between competing theories about the geographic diffusion of Internet technology. We estimate econometric models of Internet adoption at the establishment level, focusing our analysis on comparing the marginal contribution of location, industry, and complexity of application.

Our estimates examine decision-making among the largest investors in information technology (IT) in the US economy: approximately two thirds of the United States work force is employed in the type of establishments studied. Specifically, we analyze Internet adoption at 86,879 establishments with over one hundred employees; this sample comprises roughly half of US establishments of such size. The data come from a survey updated to the end of 2000. Harte Hanks Market Intelligence, a commercial market research firm that tracks use of Internet technology in business, undertook the survey.

Three central findings support the conclusions our of study:

- *Urban density theory* does not explain adoption of the Internet for simple purposes. Adoption does not increase with the size and density of a city. There is some evidence that the opposite holds. Adoption of simple Internet applications is closer to more utopian theories associated with the promise of the Internet, which we label *global village theory.*
- We reach the opposite conclusion for complex applications requiring more technical support and third party servicing, i.e., we reject *global village theory* for complex

applications. The probability that an establishment adopts complex Internet applications increases with the population and density of location, consistent with *urban density theory.*

- The type of industry found in major cities plays a key role in explaining the variance between cities, which we label *industry composition theory.* More information-intensive industries tend to cluster in urban areas. Urban density theory and industry composition theory interact in a complementary way for complex applications. This interaction could exacerbate agglomeration in use. However, because IT-intensive industries are numerous and geographically quite dispersed, so too is use of frontier technology. We find no evidence of agglomeration among simple technologies.

Besides bringing hard data to bear on the geographic variance in Internet use, our investigation also contributes novel findings to the debate about whether information technology acts as a substitute or complement to the agglomeration of economic activity (e.g., Gasper and Glaeser, 1998). Unlike some studies in this vein, we do not consider the determinants of long run equilibrium, i.e., where firms relocate after technology markets develop (e.g., Beardsell and Henderson, 1999; Kolko, 2002). Rather, we examine the short run reaction of establishments to the diffusion of a technology.

When examining substitution/complementarities, our empirical question is similar in spirit to Kolko (2000). Examining domain name registrations in the context of a periphery/central city model, he finds that users in cities of medium size and above have registration patterns consistent with those areas benefiting disproportionately from the Internet. We are also similar in spirit to Sinai and Waldfogel (2001). They examine household behavior for evidence that Internet content is either a substitute or complement to content found locally. We differ from both these papers in our focus on adoption by business establishments, as opposed to commercial domain registrations by firms or household Internet use. Moreover, our decomposition of the geographic variation of

Internet use into industry- and location-specific factors enables us test hypothesizes unexamined by prior work.

The present study is also broadly similar to our earlier work (Forman, Goldfarb and Greenstein, 2002). It established that the variance in geographical patterns of technology adoption by business differed substantially from the variance uncovered in any existing research on households or infrastructure deployment. This study differs in its focus on decomposing the factors underlying aggregate variance, and in its hypothesis testing.

We ultimately accept hypotheses based on the formulation that the Internet is a General Purpose Technology or GPT (Bresnahan and Trajtenberg, 1995). While others have hypothesized that the Internet is a GPT (e.g., see Harris, 1998), our study is the first to link this formulation to statistical analysis of adoption behavior by commercial businesses. It inspires our attention to the distinction between simple and complex applications, which rely to different degrees on local market-based support. In our characterization of how local pooled resources influence the returns to adopting complex applications, we are similar to adoption studies that examine how knowledge spillovers (e.g., Goolsbee and Klenow, 2002) and variations in education and skill level (e.g., Chun 2003; Doms, Dunne, and Troske 1997) affect demand for new technologies.

Our analysis and findings contrast strongly with the prevailing analysis inspired by the literature on the digital divide. To be sure, as in this literature, we do find that some regions are leaders and some are laggards in the use of Internet technology. However, we do not conclude that use of the Internet concentrated in a small number of places.[5] Moreover, we emphasize the sharp differences between the diffusion processes shaping

[5] For example, Zooks (2000a, b) and Gorman (2002), among many others, examine the Internet in terms of "global city theory", where a few key locations act as economic hubs for other areas. They argue that the economic effects from the diffusion of the Internet concentrate in a small number of cities.

simple and complex applications, which support a much different explanation about the factors shaping geographic variation in use.

The next two sections describe the theoretical framework, the data, and the empirical method. Section 4 describes regional variation in Internet adoption rates. Sections 5 and 6 separate out the relative importance of global village theory, urban density theory, and industry composition theory. Section 7 concludes with observations about how our findings shape the analysis of the economic returns from the diffusion of Internet technology.

2. Framework and testable hypotheses

Why are technologies, such as the Internet, adopted at different rates by different firms? We offer a framework that describes theories about how the benefits and costs of adoption vary across establishments in different locations.

Consider an establishment's decision to adopt a new technology such as Internet access or inter-firm networking capabilities. Below we will consider adoption of both a simple and a complex application of the Internet.[6] For notational simplicity we consider only a generic application of technology in this section. Establishment *i* will adopt Internet technology by time *t* if

$$NB(x_i,z_i,t) \equiv B(x_i,z_i,t) - C(x_i,z_i,t) > 0,$$

where *NB* is the net benefit of adoption, *B* is the gross benefit of adoption, and *C* is the cost of adoption. We let x_i describe geographic conditions, such as population size and density, while z_i describes industry characteristics that may impact a firm's decision to adopt Internet technology. Both features are fixed over time for establishments.

[6] Our data analysis will consider adoption of two distinct layers of Internet technology. It is easily generalizable to more than two.

Our empirical work will examine one cross section at time t. Since adoption of the Internet is rarely reversed, we are comfortable with the data-driven requirement that we suppress the time dimension. Under the standard "probit model" of diffusion (e.g., David 1969), adoption costs decline over time and timing of adoption coincides with intensity of demand. We employ the standard implication for a cross section at any point in time: The difference between adoption and non-adoption reveals the threshold between those with high and low valuations from use.[7]

We now discuss different theories about the shape of $NB(x_i,z_i)$ which give competing predictions about the role of location in the adoption of Internet by commercial establishments. Table 1 lists each of these hypotheses and their predictions.

2.1 Global village vs. urban density

Global village theory argues that gross adoption benefits increase as population size and density decrease (i.e., $dB/dx_i < 0,$ where x_i is density), and that they increase more slowly than costs ($dC/dx_i < - dB/dx_i$ *for all* x_i). Together net benefits from adoption decrease in population size and density ($dNB/dx_i < 0$). While the theory is implausible for sufficiently isolated establishments (e.g., in the Mohave desert), its proponents generally focus on the predictions for existing establishments in most urban and low density settings. Global village theory predicts that the Internet will be more common among establishments in rural areas than urban areas, all other things equal. It also predicts that advances in information and communication technology will help to decrease concentration in economic activity.

[7] Generally, see Rogers (1995). We allow the cost term C to include the opportunity cost of not adopting at some other time $s > t$, thus the net benefit condition above is both necessary and sufficient for the establishment to adopt by t. Another standard formulation would examine an establishment's decision to adopt at time t, and the equation above would be supplemented by an "arbitrage condition" (Ireland and Stoneman 1986) that it is less beneficial to adopt at any other time $s \neq t$.

This hypothesis depends on two observations. While all business establishments benefited from an increase in capabilities, establishments in rural or small urban areas will derive the most benefit from overcoming diseconomies of small local size. That is, Internet technology substitutes for the disadvantages associated with a remote location. Moreover, establishments in rural areas lack substitute data communication technologies for lowering communication costs, such as fixed private lines.

The most utopian versions of this hypothesis have received considerable exposure.[8] Yet, even the more tempered forecasts are generally treated with skepticism by most academic research on the geography of the Internet. This hypothesis has not been directly tested, and has not had much empirical verification (Forman (2002) is an exception).

Urban density theory stands in opposition to global village theory. Urban density theory argues that adoption costs increase as population size and density decrease (i.e., $dC/dx_i < 0$, where x_i is density), and that these costs increase faster than benefits ($dC/dx_i > - dB/dx_i$ *for all* x_i). Together net benefits of adoption increase in population size and density ($dNB/dx_i > 0$). Urban density theory predicts that the Internet will be less common in rural areas than urban areas, all other things equal.

There are three major factors supporting this hypothesis: (1) availability of complementary information technology infrastructure, (2) labor market thickness for complementary services or specialized skills, and (3) knowledge spillovers. These are closely related to the three major reasons given for industrial agglomeration (e.g., Marshall 1920; Krugman 1991). For example, the availability of low-cost complementary inputs,

[8] Most discussion of this hypothesis follws from Cairncross (1997, p. 1), who was an early proponent of global village theory. She states that "The death of distance as a determinant of the cost of communicating will probably be the single most important force shaping society in the first half of the next century."

such as broadband services or Internet access, will have an impact on the cost of adopting participation or enhancement.[9]

This theory has received considerable exposure, partially because the literature on the urban/rural digital divide highlights this concern.[10] For example, both Gorman (2002) and Zooks (2000a, b), summarizing the conclusions of many others as well as their own research, express this view quite strongly (see, also, Castells, 2003). They argue that Internet technology is a complement to urban agglomeration.

In comparing global village and urban density theories, we will further contrast simple purposes for business use of the Internet with complex ones.[11] The simple purposes, together labeled *participation*, relate to activities such as email and web browsing. Participation represents the most common and generic use of the Internet for basic communications. The complex purposes, together labeled *enhancement*, relate to investment in frontier Internet technologies linked to computing facilities. These technologies are often known as "e-commerce," and involve tailoring complementary changes to internal business computing processes. These investments represent the most idiosyncratic and difficult investments. We provide more precise definitions in section 3.2.

The contrast between our participation and enhancement results are informative about local adaptation costs. Bresnahan and Trajtenberg (1995) argue that the invention of a GPT like the Internet involves high fixed costs. Users typically have to adapt the GPT to their particular environments. Adoption involves a combination of (1) reproduction and (2) co-invention to meet idiosyncratic circumstances. All other things equal, when

[9] By this time period, almost all but the poorest and most remote geographic areas were serviced by dial-up Internet Service Providers (Downes and Greenstein, 2002). Yet, broadband access was disproportionately an urban technology (USDA, 2001, Crandall and Alleman, 2002)

[10] This is a particular prominent theme in the series of reports from the National Telecommunications and Information Administration (1995, 1998, 1999, 2000a, 2000b). See, also, Moss and Townsend (1997).

[11] In this choice, we follow Forman (2002), who found that investment clustered around a few key margins of behavior. For further motivation see the discussion in our companion study, Forman, Goldfarb and Greenstein (2002).

requirements and constraints are idiosyncratic, co-invention issues are expensive to address. When the issues are generic and common, co-invention expenses are lower, spread among a larger set of users.

Adaptation costs are relevant to the adoption decision for enhancement and largely negligible for participation. If the effect of increases in density on adoption benefits (e.g., dB/dx_i) is similar for both participation and enhancement, the rate of improvement in net benefits with respect to density rises faster for complex applications than for simple applications. This hypothesis predicts that enhancement will be more sensitive to increases in density than participation. This is a prediction about the comparative difference between the two types of applications, but it has no implication for whether global village or urban density theory holds for none, either, or both participation or enhancement.

2.2 Industry composition

We distinguish between three versions of industry composition theory. These theories provide potential alternative hypotheses for why the adoption of simple and complex applications is increasing in urban density. In all cases the theory argues that there is heterogeneous demand for Internet technology, and that it increases with the information intensity of the industry. Further, establishments from the same industry tend to cluster in similar places to take advantage of thicker industry-specific labor markets and other shared local resources. For the purposes of this discussion, we allow z_i to denote the IT-intensity of an industry.

In one version of industry composition theory, concentration of Internet technology-intensive activity in some locations is due entirely to agglomeration of IT-intensive industries in those locations and has little to do with population density, per se'. Previous decisions to concentrate activity could have resulted in the clustering of some types of firms in urban areas. Concentration of adoption of new Internet technology could just be an unintended by-product. This implies two testable hypotheses: (1) the concentration of IT-intensive industries will explain geographic variation in use for both simple and complex applications, and (2) location will have no marginal impact on adoption behavior beyond that explained by variation in industry composition. In other words, this version of the theory hypothesizes that $dNB/dz_i > 0$, corr(x_i, z_i) > 0 and $dNB/dx_i = 0$.

A second view asserts that both increasing population density and IT intensity may increase the likelihood of Internet adoption. Here, industry composition plays a role, but so does location. This version hypothesizes that $dNB/dz_i > 0$ and $dNB/dx_i > 0$. We explore two variants of this alternative theory.

In one variant, which we name the industry-agglomeration complements theory, location- and industry-effects may be complementary for some applications. The high quality complementary labor markets and technical service markets that are located in large urban areas reduce the costs of adopting complex applications. IT-intensive firms may be able to better able to utilize the pooled resources in large urban areas, particularly for complex applications. To summarize, $dNB/dz_i > 0$, $dNB/dx_i > 0$, and $d^2NB/ dx_i dz_i > 0$. We note that this is the theory receiving the most exposure in the literature on the digital divide.[12]

It is also theoretically possible for industry composition and urban agglomeration to be substitutes. This arises if IT-intensive industries have in-house expertise that substitutes for features associated with urban areas. In other words, $dNB/dz_i > 0$, $dNB/dx_i > 0$, and $d^2NB/ dx_i dz_i < 0$. We title this the industry-agglomeration substitutes theory. This labor market thickness story should matter much more in areas with low populations because this story relies on absolute labor market size more than on percentages. This theory has been

[12] The discussions about the concentration of industrial demand tend to focus on a narrow array of industries, such as new media, dot-coms, or electronic retailing. This also leads to a focus on Silicon Valley, Silicon Alley, and the greater Boston area. In contrast, in this study we focus on all industries and locations.

discussed as a theoretical possibility (e.g., Glaser and Gasper, 1998), but has seen little empirical verification to our knowledge.[13]

3. Data and method

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. Harte Hanks Market Intelligence (hereafter HH) collects this information to resell as a tool for the marketing divisions at technology companies. Interview teams survey establishments throughout the calendar year; our sample contains the most current information as of December 2000.

Harte Hanks tracks over 300,000 establishments in the United States. Since we focus on commercial Internet use, we exclude government establishments, military establishments and nonprofit establishments, mostly in higher education. Our sample contains all commercial establishments from the CI database that contain over 100 employees, 115,671 establishments in all; [15] and HH provides one observation per establishment. We will use the 86,879 clean observations with complete data generated between June 1998 and December 2000. We adopt a strategy of utilizing as many

[13] One exception is Kolko (2002), who examines in agglomeration in the location decisions of IT-intensive firms.
[14] This section provides an overview of our methodology. For a more detailed discussion, see Forman, Goldfarb, and Greenstein (2002).
[15] Previous studies (Charles, Ives, and Leduc 2002; 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, while our participation estimates may overstate participation relative to the population of all business establishments.

observations as possible because we need many observations for thinly populated areas.[16] This necessitates routine adjustments of the data for the timing and type of the survey given by HH. Table A1 in the Appendix compares the HH data with the Census data. In general, the samples are close, so most adjustments are small.

3.1. Sample construction and statistical method

Our endogenous variable will be y_j, the value to establishment j of adoption. The variable y_j is latent. We observe whether or not the establishment makes a discrete choice, for example, chooses participation or enhancement. In either case, the observed decision takes on a value of either one or zero. We will define these endogenous variables more precisely below.

In our base specification we assume that the value to an establishment j of adopting the Internet is

$$(1)\quad y_j = \sum_i \alpha_i d_{ij} + \sum_l \beta_l d_{lj} + \sum_t \gamma_t d_{tj} + \sum_{t>1995} \delta_t d_{tj} d_{pj} + \sum_m \phi x_{mj} + \sum_q \lambda w_{qj} + \varepsilon_j$$

where d_{ij} and d_{lj} are dummy variables indicating the industry and location of the establishment, d_{tj} indicates the month in which the establishment was surveyed, and d_{pj} indicates whether the establishment responded to the long survey.[17] The variables x_{mj} and w_{qj} denote other location-specific (e.g., population size and density) and establishment-specific variables (e.g., establishment size and dummies indicating single- or multi-establishment firm). In variations of the model, we may allow for interactions among these

---

[16] If we were only interested in the features of the most populated regions of the country, then we could easily rely solely on the most recent data from the latter half of 2000, about 40% of the data. However, using only this data would result in a very small number of observations for most regions with under one million in population.

[17] HH used two surveys. One asked for more details on IT use than the other. We interact the long survey dummy with time. See Forman, Goldfarb and Greenstein (2002) for detail.

variables. If we assume the error term ε_j is i.i.d. normal, then the probability that establishment *j* participates can be estimated with a probit regression.

We use this model for two research purposes. Our first purpose is descriptive. We illustrate average tendencies for particular establishments in particular locations at a particular point in time. We then weight observations using Census County Business Patterns data to obtain a representative sample. We do this to establish and illustrate the extent of overall variation in adoption propensity. For the average estimates in Tables 2, 3, and 4, we calculate predicted probabilities of adoption for each establishment *as if it were surveyed in the second half of 2000 and were given the long survey*. The x_{mj} and w_{qj} are not included in this specification.

Our second (and core) purpose is to test competing hypotheses. We analyze the marginal contribution of different factors that shape adoption decisions at the establishment. We report marginal effects from a variety of different specifications, where the model listed above is our base case. The coefficients on α, β, and ϕ are weighted to give a representative sample. We display these results below in Tables 5 through 9 and Figures 1 through 4.

Two econometric assumptions support the estimates of marginal effects:

- **Exogenous location:** We examine short-run marginal effects of industry and location variables on the decision to invest in Internet technology. To identify these effects, we assume that the location of an establishment is exogenous. We argue this assumption is supported by the (ex-ante) unexpected rapid diffusion of the Internet, and through robustness checks.

First, this assumption is plausible. As noted earlier, the widespread diffusion of the Internet took most commercial establishments by surprise. Thus, firms did not make establishment location decisions in anticipation of the Internet. Moreover, we observe short-run adoption decisions five years into the diffusion of the Internet, before medium and large establishments had time to relocate.

Second, we can test this assumption directly by comparing results between our entire sample of establishments and a special sub-sample of establishments who (we are certain) fixed their locations prior to the availability of the commercial Internet, i.e., prior to 1995. Since we find that the key estimates do not differ between these two samples, we infer that the potential endogeneity of establishment locations does not alter our inferences about the influence of location on adoption of Internet technology.

- **Simultaneity bias:** Our base econometric specification assumes that the adoption decision of one establishment is independent of every other. This assumption is questionable for multi-establishment firms in which a central executive decision maker (e.g., a CIO) possibly coordinates the choice to adopt or not adopt for each establishment under his domain. Depending on a wide variety of factors, adoption decisions at establishments from the same organization could be either substitutes or complements for one other. While understanding that this relationship is of independent interest, it also lies outside the scope of this study. For purposes of this study, we are concerned that simultaneity influences the coefficient of interest, the estimate of location on adoption at each establishment.

We address these concerns directly by characterizing the decisions of related establishments at other locations in a reduced form way, then measuring whether this alters the estimate of the coefficient on location, instrumenting for decisions elsewhere. Our focus will be on whether our inferences about the influence of location on adoption of Internet technology are robust to introducing simultaneity into the estimation. We will find that, no matter how we measure it, our key results do not change.

3.2. Defining participation and enhancement

As a GPT, Internet technology is employed in many different uses and applications. Our sample includes at least twenty different types of Internet technology, from basic access to software for TCP/IP-based Enterprise Resource Planning (ERP). Moreover, there are considerable differences in the applications used across establishments. We bracket the possibilities by identifying two types of applications, one simple and the other complex.

Participation is affiliated with basic communications, such as email use, browsing, and passive document sharing. It represents our measure of the minimal investment required to do business on the Internet. It is emphasized in many studies of "universal service" in new technologies.[18] Geographic differences in participation, such as urban/rural divisions, are important drivers of policy decisions in this area.

Enhancement, on the other hand, is affiliated with IT that either changes existing internal operations or implements new services. Enhancement is linked to the productive advance of firms and the economic growth of the regions in which these firms reside. It usually arrives as part of other intermediate goods, such as software, computing or networking equipment. Benefits accrue to the establishment that employs enhancement through the addition of competitive advantage. The costs and delays of this activity vary.[19]

Identifying participation was more straightforward than identifying enhancement. We identify participation when an establishment has basic Internet access or has made any type of frontier investment.[20] The establishment survey gives plenty of information about these activities, so we identify participation with confidence.

---

[18] See, e.g.,Cherry, Hammond and Wildman 1999, Compaine 2001, Noll et al. 2001.

[19] Such applications often involve complementary organizational change to be used successfully. See, for example, Hubbard (2000), or Bresnahan, Brynjolfsson, and Hitt (2002).

[20] To be counted as participating in the Internet, an establishment must engage in two or more of the following activities: (1) have an Internet service provider; (2) indicate it has basic access; (3) use commerce, customer service, education, extranet, homepage, publications, purchasing or technical support; (4) use the Internet for research, or have an intranet or email based on TCP/IP protocols; (5) indicate there are Internet

In contrast, enhancement activity is less transparent in the survey. We look for indications that an establishment must have made the type of investment commonly described in books on e-commerce. We identify enhancement from the presence of substantial investments in e-commerce or e-business applications. The threshold for "substantial" is necessarily arbitrary within a range.[21] To provide confidence that we are measuring substantial investment, we look for commitment to two or more of the following projects: Internet-based enterprise resource planning or TCP/IP-based applications in customer service, education, extranet, publications, purchasing or technical support.[22]

3.3. Descriptive statistics

To obtain a representative sample, we compared the number of establishments in our database to the number of establishments in the Census. We calculated the total number of establishments with more than 50 employees in the Census Bureau's 1999 County Business Patterns data and the number of establishments in our database for each two-digit NAICS code in each location.[23] We then calculated the total number in each location. This provides the basis for our weighting. The weight for a given NAICS in a given location is

---

users or Internet developers on site; or (6) outsource some Internet activities. We looked for two or more activities to guard against "false positives". This was a minor issue as most respondents responded affirmatively to many of these criteria.

[21] We tested slight variations on this threshold and did not find qualitatively different results.

[22] In brief, an establishment is counted as enhancing business processes when two or more hold: (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, web development, or web server; (5) the establishment has an Internet server that is a UNIX workstation or server, mainframe, or minicomputer, or has 5 or more PC servers, or has Internet storage greater than 20 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, Goldfarb, and Greenstein (2002).

[23] We use 50 employees because potential differences between different times for taking the survey mean that firms could grow after the Census and therefore be in the CI database. It was necessary to be inclusive for the weighting because some small rural areas had less than three firms in both the Census and the CI database; and therefore if one firm grew from the time of the Census to the time of the CI survey, the weightings would be difficult to interpret. The results are robust to weighting by firms with more than 100 employees in the Census and those with more than 25 employees. This is not surprising given the high correlation between these values.

$$(2)\quad \frac{Total\,\#\,of\ census\ establishments\ in\ location-NAICS}{Total\ \#\ of\ census\ establishments\ in\ location}\cdot\frac{Total\,\#\,of\ establishments\ in\ our\ data\ in\ location}{Total\,\#\,of\ establishments\ in\ our\ data\ in\ location-NAICS}$$

Each location-NAICS is given its weighting from its actual frequency in the Census. In other words, if our data under-samples a given two-digit NAICS at a location relative to the Census then each observation in that NAICS-location is given more importance. Appendix table A.1 compares our sample to the Census data.

In Table 2 we present average rates for participation and enhancement for the US. Participation by establishments within the sample is at 80.7% (see Unweighted Average in Table 2). The sample under-represents adopters. Our estimate of the economy-wide distribution, using the true distribution of establishments from the Census, is 88.6% (see Weighted Average in Table 2). Enhancement has been undertaken by 11.2% of our sample and 12.6% of the true distribution.

4. The dispersion of participation and enhancement

In this section, we argue that there is considerable variation across locations in the propensity to adopt Internet technologies. Table 3 shows participation and enhancement rates across types of locations in the United States. Because there has been little prior work on variation in use of the Internet by business, these descriptive findings are not widely appreciated. In previous work (Forman, Goldfarb and Greenstein, 2002), we contrasted them with other studies of the geographic variation in household use of the Internet and infrastructure deployment. We reproduce it here because, on a broad level, this table motivates the present study. Table 3 shows sizable differences in participation and enhancement between large urban, small urban, and rural areas. On the surface, this evidence supports either urban density theory or industry composition theory. We see that large MSAs have very high participation rates, averaging 90.4%. Participation rates in medium-sized MSAs and rural (non-MSA) areas are lower at 84.9% and 85.1%, respectively. In small MSAs the participation rates are even lower, 75.5% on average.[24]

The disparities in adoption rates for enhancement are even greater (again, see Table 3). Large MSAs have relatively high adoption rates, with an average of 14.7%. In medium MSAs, adoption averages 11.2%. In small MSAs the rates are even lower, 9.9% on average. Average adoption rates in large MSAs are almost one-third greater than in medium MSAs. Once again, these averages suggest that urban density theory or industry composition theory may hold. Clearly there is considerable variation in adoption propensity by city size. What produces such variance?

In Tables 4a and 4b we provide an overview of participation and enhancement adoption results for the largest economic areas in the United States. Once again, these results motivate our study. In brief, this summarizes our endogenous variable in different locations.

We list the estimates for Metropolitan Statistical Areas (MSAs) with over one million people, in order of highest to lowest adoption rates.[25] As we do in all of our tables, we list the standard errors and number of observations to identify the degree of statistical confidence in the estimates.[26] (For comparison, Tables 4a and 4b also list the marginal effect of location on adoption, which we will discuss later.)

---

[24] 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*.
[25] When two or more MSAs are part of the same urban environment, the census combines them into CMSAs. For example the Dallas-Fort Worth CMSA contains both Dallas and Forth Worth. In Table 3 we present the CMSA results rather than the individual MSA results when an MSA is part of a CMSA.
[26] These are computed using the delta method.

In Table 4a, we show that participation is high in major urban locations. Virtually all establishments in the major urban areas are participating. We estimate that of the forty-nine MSAs, thirty-five are above 90%. All but five are within a 95% confidence interval of 90%. Nevertheless there are big differences among metropolitan areas at the extreme. In Table 4b we examine the use of enhancement at establishments in MSAs with over one million people. All but one are within a 95% confidence interval of the national average of 12.6%. The top ten include a set of areas that partially overlaps with the list in Table 4a. (Five of the top ten are also in the top ten for participation.) Still, the differences between the lowest adopting areas and the highest adopting areas are substantial.

These tables illustrate considerable variation in adoption propensity by city size and between cities of the same size. What produces such variation?

5. The marginal impact of location on Internet adoption

In this section, we estimate equation (1), focusing on testing between global village and urban density theories. We weight observations by the inverse probability that an establishment will appear in our sample. To be precise, the weight for each observation is the total number of establishments in a state/NAICS in Census County Business Patterns data divided by the number of establishments in the state/NAICS in our sample multiplied by controls for sampling the same establishment twice.

Table 5 shows the roles of population and density in the adoption decision. Part A presents the coefficients of the probit regressions. Part B presents the marginal effects. All probit regressions include dummy variables for 3-digit NAICS, the month the data were collected, survey type, survey type interacted with month, and whether or not the establishment was part of a multi-establishment firm. Employment and employment squared were also included as controls. Population was measured at the MSA level and density at the county level.

For columns 1 and 5, we use non-urban (hereafter termed *rural*) state areas for the base. For columns 2, 3, 6, and 7, we include a "rural area" dummy for rural areas, since no meaningful population figures exist for these areas. In columns 4 and 8 we include population density for all urban and rural areas using low-density areas as the base.

5.1 The marginal impact of location

From Table 5, it is clear there is no support for the urban density theory in participation. Controlling for industry and firm characteristics, location size and density have little impact on the decision to adopt at the participation level. If anything, the effects of location size and density support global village theory, but the impact of geography is of limited economic and statistical significance. In column 1, we show that medium and large MSAs are 0.5% to 1.0% less likely to have adopted participation by the end of 2000. However, the effect is only significantly different from rural areas for medium MSAs. Moreover, this effect is only of marginal economic significance as participation rates average 88.6%.

In column 2, we identify the effects of size through a variable that captures the effects of increases in population in urban areas. Increases in population size decrease the probability of participation, though the effects are statistically insignificant. In column 3 we include a squared population term. In this formulation, the linear term remains statistically insignificant, while the squared term is significant, albeit very small. This model implies that the effects of population will turn negative once urban areas exceed 7.039 million, a threshold that is larger than all but the five largest urban areas. In column 4 we include dummies for population density. This alternative specification gives very similar results.

Variation in population density does not affect participation by more than 1%, and it is always statistically insignificant.

The effects of population size and density on enhancement support urban density theory. Column 5 in Table 5B shows that establishments in medium and large MSAs adopt enhancement at a rate 0.8% to 1.1% higher than rural areas. Column 8 shows that establishments in medium- and high-density regions adopt enhancement at a rate 1.0% to 1.5% more. All of these effects are statistically significant. They are economically significant in light of the average enhancement rates of 12.6%. While column 6 suggests that a linear population term has little effect on enhancement, column 7 shows that population will have a statistically and economically significant positive effect for all metropolitan areas below 8.8 million in size (all but New York, Los Angeles, and Chicago).

Together these results support the key prediction of GPT theory about the comparative relationship between complexity of application and geographic variance in use. The probability that an establishment adopts the Internet for enhancement is more sensitive to geographic variation in density than the similar probability for participation. We interpret this as evidence that the applications more dependent on third-party support and complementary services are most costly to deploy in less dense locations.

How does the variance in location contribution vary by city size? In Figures 1 and 2 we graph the marginal effect of location in the baseline probit in model (1) to reinforce the results of Table 5.[27] We divide locations into four types: large MSAs, medium MSAs, small MSAs, and statewide rural (non-MSA) regions. In Figures 1 and 2 we plot the kernel

[27] This probit is not depicted in any table. We identify the effects of population size and density directly through the location-specific dummy variables.

density estimates of the effects of location on participation and enhancement, respectively.[28] We use Epanachnikov kernels with "optimal" bandwidths.

In Figure 1 small MSAs and rural areas have a fatter right tail, while the density for large MSAs reaches its peak below any of the three other classes of geographic areas. In all, this figure provides further support for global village theory: increases in local population size and density do not increase the likelihood of participation adoption. If anything, they lower it.

In Figure 2, it is clear that the density estimate for large MSAs stochastically dominates those for small and medium MSAs and rural areas. This provides a visual depiction of the results in Table 5 that urban density theory better describes the geographic diffusion of enhancement than global village theory.

Table 6 presents summary statistics on the marginal effects of the same regressions. Again, the results show that establishments in larger MSAs are less likely to adopt participation and more likely to adopt enhancement.

We checked our results for a variety of robustness issues. As noted, we were concerned that establishment location decisions might be endogenous with improvements in communications technology. We re-estimated the model using only establishments that had been added to the HH database prior to 1995, the year in which Internet technology began to diffuse widely to businesses. Although this restricted the size of our sample substantially (to 23,436 observations), the basic results remain the same. The correlation coefficients between our baseline marginal effects and those using pre-1995 data are 0.829 for participation and 0.997 for enhancement. Qualitative results did not change.

We tried a number of other robustness checks. For one, we worried about omitted variables. We experimented with a variety of different specifications by using different

[28] The omitted MSA is San Jose, the top MSA in adoption of enhancement.

location variables (e.g., CMSA dummies), different firm controls (e.g., revenue, private/public), and alternative measures of population size and density. We also worried about how weighting the probit model would affect our results. We tried weighting the probit regressions by 3-digit NAICS/states, 2-digit NAICS/MSAs, as well as no weighting at all. In all cases the results remained qualitatively the same; the correlation coefficients between our baseline coefficient estimates and the alternative specifications were between 0.88 and 0.95 for participation and 0.78 and 0.90 for enhancement.[29]

5.2 Location and multi-establishment firms

Multi-establishment firms often adopt new communication technologies at some, but not all, of their establishments. Multi-establishment firms will choose to locate Internet technology in the least-cost locations, implying that the effects of greater population size and density (urban density) will be more important to adoption decisions for establishments that are part of multi-establishments firms. This will be particularly true for complex enhancement technologies, where co-invention costs are higher. In this section, we systematically examine how multi-establishment status changes the marginal returns to location. We find the results to be in the expected direction, but not sufficiently large to alter the evidence for or against urban density or global village theory.[30]

First, we show that multi-establishment status does predict adoption. The results in Tables 7a and 7b support the hypothesis that the effects of greater population size and density are larger (more positive) if the establishment is part of a multi-establishment firm.

[29] We also explored whether systematic establishment differences across geographic locations are driving our results. Though unobservable establishment differences could play a role, we were unable to uncover any pronounced observable establishment differences. Using weighted data, establishments in large MSAs are larger (12.8% of establishments with >500 employees versus 9.0% for small MSAs and 9.9% for rural areas) and more likely to be multi-establishment (48.7% multi-establishment versus 43.9% for small MSAs and 33.4% for non-MSAs). However, when using unweighted data much of the differences disappear (12.7% of establishments in large MSAs >500 employees versus 12.1% in small MSAs 13.4% in rural areas; 46.3% of establishments in large MSAs multi-establishment versus 46.8% in small MSAs and 40.8% in rural areas).

[30] To our knowledge, this study is the first to address how multi-establishment status affects technology adoption. Note, however, that our ability to do this comprehensively is restricted by our data. We do not observe all of an organization's establishments. We observe only those with more than 100 employees.

Equivalently, the effects of smaller population size and density are greater for single-establishment firms. This is particularly true for enhancement technologies.

Column 1 of Table 7b shows that when a multi-establishment dummy is interacted with MSA dummies the non-interacted medium and large MSA dummies now both have a statistically significant marginal effect of –1.3% and –1.0% respectively. There is no statistically or economically significant effect in the interaction terms themselves. When multi-establishment is interacted with population, there is a statistically significant but small marginal impact of 0.042% per 100,000-person increase in population.[31] The effect of population itself has a more negative impact than in Table 5.[32] Similar results hold using population density rather than size.

The economic significance of multi-establishment is larger for enhancement. Interactions of multi-establishment dummies with population size and density weaken the positive effects of non-interacted population variables. In many cases marginal effects become smaller or less statistically significant. In all the columns the interaction terms suggest that the effects of population size and density are greater for multi-establishment firms.

The economic effects can be substantial. Columns 5 and 8 suggest that establishments located in large MSAs or densely populated counties and that are part of multi-establishment firms are 2.2% to 2.3% more likely to adopt enhancement than stand-alone establishments in the same locations. These marginal effects are sizable compared to typical enhancement rates of 13%. The marginal effects of interacting multi-establishment

[31] This calculation is not shown in the table.

[32] These results do not reflect any collinearity between multi-establishment and urban areas. Multi-establishment dummies had a statistically and economically significant impact in the baseline regressions in Table 5; the marginal effect was between –2.6% and –2.8%. Moreover, the correlation between multi-establishment status and location in an MSA positive but small (0.0427).

with MSA population (in column 6) are statistically significant, but only 0.025% per 100,000 person increase in population.

The discussion above ignores potential simultaneity bias arising from establishment-level analysis of adoption decisions in multi-establishment firms. We extended our statistical model to include variables capturing the behavior of other establishments within the same firm. In particular, we added variables measuring the percentage and total of other establishments within the same firm adopting the dependent variable (e.g., participation or enhancement). Because these variables are likely to be correlated with unobserved factors affecting the decision to adopt participation and enhancement, we also used nonlinear instrumental variable techniques. For instruments, we used average population and density of other establishments in the same firm. These should be correlated with adoption decisions at the firm's other establishments, but not at the establishment of interest.

We first show whether our baseline estimates (without multi-establishment interactions) are robust to the inclusion of other establishment decisions. Appendix Table A.2 shows the marginal effects of probit regressions that add other establishment adoption decisions to the models in Table 5. These regressions are performed with and without IV. These robustness checks make little difference to the estimated relationship between population density and Internet adoption, our test for global village and urban density theory. Table A.2a shows that variables capturing the percentage of establishments with participation and enhancement come in positive and significant in weighted probit regressions, however their significance disappears once we instrument in Table A.2b. We interpret the probit regressions without IV as picking up unobserved heterogeneity, which is ultimately eliminated in the IV probit regressions. The new variables have little effect on the population marginal effects. Moreover, statistical significance of our location variables is retained in the IV version of this model.

Similarly, Appendix Table A.3 shows that the inclusion of other establishments' decisions has almost no impact on the estimates of our multi-establishment interaction models in Table 7. The new variables have the same pattern as in Table A.2: positive and significant in probit regressions without IV, insignificant in probit regressions with IV. We conclude that simultaneity of decisions does not significantly bias our results.

6. Industry Composition

The differences between the average adoption rates in Table 3 and the marginal effects in Table 5 show that the effects of location on participation and enhancement fall if we include controls for establishment size, industry, and firm status. In Table 3, large MSAs have almost a 15% higher participation rate and 5% higher enhancement rate than small MSAs. In Table 5, locating in a large MSA rather than a rural area reduces the probability of participation by 0.6% and increases the probability of enhancement by 1.1%.

The large differences in adoption rates between large and small urban areas in Table 3 reflect differences in industry composition across locations. Industry composition explains much more of the variation in participation and enhancement rates than location. Once industry is controlled for, the incremental contribution of location in the probit regressions is small. This is shown in Table 8. The pseudo-R^2 of a probit for participation including only location dummies is 0.1526, whereas the pseudo-R^2 of a probit with only industry dummies is 0.2251. Adding location dummies to a probit that includes industry dummies barely improves fit, from 0.2251 to 0.2339.

Enhancement displays a similar pattern. Location dummies explain only 0.0347 of the variation in enhancement, industry dummies explain 0.0591, and the combination of industry and location dummies explains 0.0672. While there remains a great deal of unexplained variation in our results, we conclude that an establishment's industry explains more of the variation in Internet use than geographic location.

6.1. What does industry composition explain?

The three theories that emphasize the importance of industry composition assert that leading industries concentrate in large urban areas. To test this hypothesis, we separated establishments by geographic location type (e.g., rural, small, medium, and large MSA) and calculated the kernel density of industry marginal effects for each type of location. The underlying marginal effects are the same across all four types of locations. However, the densities of each marginal effect differ because of differences in industry composition across locations. We did this for both participation and enhancement.

In Figure 3, we show the kernel density estimates of the marginal effects of industry by geographic area for participation.[33] Lead-user industries tend to be concentrated in large geographic areas. The average of the marginal effects of industry in rural and small MSAs is –18.7% and –20.2%, while the average of the marginal effects for medium and large MSAs are –18.8% and –16.9%. Except in comparing rural and medium MSAs, these averages are significantly different from one another at the 1% level. Large MSAs tend to have more lead-user industries, even for participation.

Figure 4 shows that lead users of enhancement are even more skewed toward large MSAs. Rural areas and small MSAs have the highest densities along the left tail of the distribution, whereas large and medium MSAs have higher densities along the right tail. The average marginal effect of industry on enhancement adoption is increasing in location

[33] All industry results are unweighted. The omitted industry is information and data processing (NAICS 514). We use Epanachnikov kernels with bandwidth of 0.05 for participation and 0.005 for enhancement. These are wider than "optimal" bandwidths. Optimal bandwidths fail in this case as there are thousands of observations but the only 81 possible values as there are 81 relevant 3-digit NAICS levels. Therefore the optimal bandwidth does almost no smoothing.

size: –8.0% in rural, –7.8% in small MSAs, –7.7% in medium MSAs, and –7.4% in large MSAs. Again, these averages are all significantly different from one another at the 1% level. The bulk of the variation in Table 3 reflects differences in industry composition between small and large MSAs, rather than other location-specific benefits of locating in large urban areas.

We conclude that large urban areas are comprised of establishments with a disproportionate tendency to be information intensive. To be concrete, within large MSAs, 27.5% of establishments are in industries that are part of the top quartile of adopters, compared to 19.0% of establishments in small MSAs. The industries in the upper quartile are traditionally information intensive, such as utilities, finance and insurance, company headquarters, professional and scientific services, electronics manufacturing, and wholesale trade.[34] The geographic dispersion of establishments from these industries favored large urban areas prior to the diffusion of the Internet and largely contributed to higher rates of participation and enhancement in large urban areas.

Two conclusions emerge. First, this supports the importance of controlling for industry composition when testing between global village and urban density theory. Second, inferences about the relationship between IT and economic activity are fraught with omitted variable biases in the absence of such controls. We note that this factor is missing from all existing analysis about the geography of Internet use.

6.2. Are industry and location complements or substitutes?

Table 8 and Figures 3 and 4 suggest that industry composition theory explains a major part of establishment decisions to adopt Internet technology. However, they are unable to represent whether industry and location effects are complements or substitutes. IT-intensive industries benefit disproportionately from spillovers and other pooled

[34] For more detail, see Forman, Goldfarb and Greenstein (2002).

resources in large urban areas; however, these industries may have expertise in-house that substitutes for the thicker labor markets associated with large cities.

To examine the industry-agglomeration substitutes and complements hypotheses, we rerun the probit regressions in Table 5 with additional variables controlling for (1) whether the establishment is in a lead-user industry and (2) interactions of this lead user dummy with MSA size dummies. We define lead-user industries in one of two ways: (1) the top quartile of participation or enhancement adopters among 3-digit NAICS industries in our study or (2) the Department of Commerce (2002) top 15 IT-using industries as reported in Daveri and Mascotto (2002). [xx Avi, I changed this slightly, is this still correct? I got it from p. 5 of their paper xx] Both measures of IT intensity have strengths and weaknesses. The measure based on the top quartile selects on the dependent variable; the measure from Daveri and Mascotto is based on a more general measure of IT intensity than the Internet. Consequently, these are not final tests. We present these results as descriptive evidence that may support either a complement or substitute relationship between industry and location effects,. To further supplement our analysis, we later examine whether establishments in lead user industries (defined by high marginal effects), also tend to be located in favorable locations (locations with high marginal effects). In other words, we examine whether "good" industries are located in "good" locations.

Using the data on lead Internet adopters, Table 9A shows that there is little evidence of a complementary relationship between industry and location in participation; if anything, they are substitutes. An establishment in a top-25 NAICS and large MSA is 2.6 percent more likely to adopt participation than an otherwise equivalent top-25 establishment in a rural area. However, large MSAs are 2.8 percent less likely to adopt than small MSAs, although the difference is not statistically significant. The NAICS-level controls likely explain the lack of significance on the IT-intensive industry dummy (under both definitions). Because they are based on a more general measure of IT use, industry-location interactions in Table 9B are less significant than in Table 9A. However, they tell exactly the same story. An establishment in a lead-user SIC and large MSA is 1.4 percent less likely to adopt than an otherwise equivalent establishment in a small MSA.

In contrast, Table 9 shows a strong complementary relationship between industry and location for enhancement. Table 9A shows that an establishment in a top-25 NAICS and large MSA is 20.0 and 27.3 percent more likely to adopt enhancemenet than an otherwise equivalent top-25 establishment in a rural or small MSA, respectively. Such an establishment is equally likely to adopt enhancement as an equivalent establishment in a medium MSA. The results in based on a more general measure of IT-intensity are again weaker, but tell the same general story. Table 9B shows that an establishment in a lead-user industry and large MSA is 0.2 percent more likely to adopt enhancement than an otherwise equivalent establishment in a small MSA. Moreover, the positive coefficient on the interaction of lead-user industry and large MSA is the only statistically significant interaction in the regression. That is, as suggested by the industry-agglomeration complements theory, industry and location are complements for complex applications, but have little relationship for simple applications.

As an alternative way of examining whether industry and location effects tend to complement or substitute one another, we compare median industries by IT use across cities. This is not an explicit test for complementarities, but rather another way of showing whether establishments in IT-intensive industries tend also to be located in favorable industries.

We calculate correlations between the marginal effects of the median industry within each urban area with those of the urban areas themselves. The results are consistent with our findings in Table 9. For participation, the marginal contribution of the median industry in a location is uncorrelated with the marginal contribution of the location itself (ρ=-0.0214). However, this result disguises a large difference between large and medium MSAs on the one hand and small MSAs and rural areas on the other. The correlation between the marginal contribution of median industry and location is significantly positive (ρ=0.307) for large and medium MSAs but significantly negative (ρ=-0.211) for small MSAs and rural areas. For larger population locations, good cities do have good industries for participation; yet for smaller areas the opposite is true.

For enhancement, there do seem to be complementarities between cities and locations (ρ=0.161). These complementarities do not vary much by city size. Regardless of size, good industries are in good cities and good cities are dominated by good industries. Cities and IT appear to be complements for enhancement, but not in the case of participation, especially in low population areas. This is consistent with the industry-agglomeration complements theory, which emphasizes complementarity for complex applications. We interpret this complementarity as a likely result of spillover effects in using frontier technologies. The exception is as interesting as the more general finding. In low population areas, favorable locations likely only help adoption in firms without in-house expertise. In that case, location and industry become substitutes. This result is potentially consistent with industry-agglomeration substitutes theory, which is most relevant for small urban areas.

7. Conclusions

Has the Internet realized its promise of reducing the importance of location to economic activity? In this paper we tested competing views by examining hard data about the short-run decisions of firms to invest in the Internet.

By 2000, participation activities such as email and web browsing had diffused almost everywhere. For these simple technologies, there was no evidence that urban density held: industry composition explains the higher levels of participation adoption in urban areas. Once industry composition was controlled for, we found that the variation across locations is best explained by the global village theory. Moreover, we found some evidence of substitution between IT-intensity and location density: IT-intensive users in rural locations were the most likely to adopt participation technologies. For this technology with low adaptation costs, we find little evidence of complementarities between industry and location.

For complex enhancement technologies, adoption behavior is best explained by urban density theory. We find evidence of complementarities between industry and location effects in the adoption of enhancement: IT-intensive firms found greater benefits than other firms from pooled resources in large cities.

The geographic variation in use was consistent with GPT theory: enhancement costs are more sensitive to variation in density than are participation costs. Adopters of participation faced low technical hurdles to implementation, while adopters of enhancement faced high costs. Establishments overcame these costs because they had experience with overcoming technical and co-invention costs, had access to rich complementary resources through local markets, or both.

Did the Internet exacerbate geographic inequalities, diffusing disproportionately to urban areas with complementary technical and knowledge resources? Our research shows that the answer is no, even for complex applications that enhance business computing processes. More precisely, there were forces leading to concentration of complex applications in urban areas, but these were not concentrated in a few cities. Users of complex applications are widely dispersed to many industries.

Of more relevance to economic growth, the geographic pattern of adoption for enhancement is quite understandable as an economic matter if these applications have high value and potentially high co-invention costs, which differ depending on local conditions. In smaller MSAs and rural areas, thin technical labor markets alone could drive up costs of operating facilities employing frontier Internet technology. These effects are particularly pronounced for multi-establishment firms. Because the investment is linked to competitive settings, multi-establishment organizations, if they had a choice, would implement new business processes in the more hospitable settings of major urban areas. In addition, multi-establishment organizations would hesitate to open their own complex Internet facilities in rural areas until the costs are lowered. In any case, variation in the availability of complementary resources would lead to more use of enhancement in major urban areas. Particularly for multi-establishment organizations, the outcome is not alarming at all.

Our findings provide several avenues for future research. First, our conclusions apply only to medium to large establishments. We defer to future research to examine small establishments and newly founded firms, who may face a different array of benefits, and may have diminished access to internal resources for idiosyncratic adaptation costs. It is already apparent from existing papers that participation is lower on average in small firms,[35] so we speculate that smaller firms will be more sensitive to geographic variation in local complementary resources than found here.

Second, our findings suggest broadly that variations in co-invention costs across technologies and locations shaped the diffusion of Internet technology. Research on the role of co-invention costs on Internet diffusion has been hampered by the binary nature of the adoption decision considered in many studies, including this one. Future work should analyze variations in firm co-invention costs, emphasizing in particular the impact of variation in labor market conditions, spillovers, and markets for technical support.

[35] For the beginnings of such research, see Atrostic and Gates (2001) on manufacturing establishments, and Buckley and Montes (2002) or Bitler (2002) for analysis of small business computer use.

Third, our findings have implications for variation in the dollar value of investment across location and industries and the net returns from those investments. The standard diffusion model of adoption implies that magnitudes of investment should follow patterns similar to the patterns for the binary adoption decision. Hence, we speculate that the flow of investment dollars to correlate positively with the rankings of location and industries uncovered in this study. Related, if this model is correct, the investment dollars affiliated with the commercialization of the Internet were widely dispersed throughout locations and industries in the United States. This speculation awaits confirmation with data about investment behavior beyond adoption.

References

Atrostic, Barbara, K., and John Gates. 2001. U.S. Productivity and Electronic Business Processes in Manufacturing. Working Paper #01-11. Center for Economic Studies, US Census Bureau.

Beardsell, M.; Henderson V., 1999, "Spatial Evolution of the Computer Industry in the USA." *European Economic Review*, 43(2), pp. 431-456.

Bitler, Marianne, P. (2002), "Computer Adoption by Small Businesses: Who Adopts?," Mimeo, Rand Corporation, Santa Monica, CA.

Bresnahan, Timothy, and Manuel Trajtenberg. 1995. General Purpose Technologies: 'Engines of Growth'? *Journal of Econometrics.* 65 (1): 83-108.

Bresnahan, Timothy, Erik Brynjolfsson, and Lorin Hitt. 2002. Information Technology, Work Organization, and the Demand for Skilled Labor: Firm-Level Evidence. *Quarterly Journal of Economics* 117 (February): 339-376.

Buckley, Patricia, and Sabrina Montes, 2002, *Main Streat in the Digital Age: How Small and Medium-sized Business Are Using the Tools of the New Economy,* Department of Commerce, at http://www.esa.doc.gov/reports.cfm.

Cairncross, Frances, 1997. *The Death of Distance.* Cambridge, MA: Harvard University Press.

Castells, Manuel, 2003. The Internet Galaxy, Reflections on the Internet, Business and Society, Oxford University Press.

Census. 2002. Detailing Tabulations of Manufacturing E-Business Process Use in 2000. Survey Release from United States Department of Commerce. See www.census.gov/epcd/www/ebusiness.htm.

Charles, S., M. Ives, and A. Leduc. 2002. Embracing E-Business: Does Size Matter? Research Report, Statistics Canada.

Cherry, Barbara, Alan H. Hammond, and Steve Wildman. 1999. *Making Universal Service Policy: Enhancing the Process Through Multidisciplinary Evaluation*. Mahwah, NJ: Lawrence Erlbaum Associates.

Chun, Hyunbae. 2003. "Information Technology and The Demand For Educated Workers: Disentangling the Impact of Adoption Versus Use." *The Review of Economics and Statistics* 85(1): 1-8.

Compaine, Benjamin. 2001. *The Digital Divide: Facing a Crisis or Creating a Myth?* Cambridge, MA: MIT Press.

Crandall, Robert & Alleman, James H. 2002. *Broadband: Should We Regulate High Speed Internet Access?* AEI-Brookings Joint Center for Regulatory Studies, Brookings Institution Press: Washington DC.

Daveri, Francesco, and Andrea Mascotto. 2002. The IT revolution across U.S. States. Working Paper. IGIER.

David, Paul A. 1969. "A contribution to the Theory of Diffusion" Stanford Center for Research in Economic Growth, Memorandum No. 71, Stanford University.

Doms, Mark, Timothy Dunne, and Kenneth R. Troske. 1997. "Workers, Wages, and Technology." *The Quarterly Journal of Economics* 112(1): 253-290.

Downes, T.; and Greenstein, S., 2002, "Universal Access and Local Internet Markets in the U.S." *Research Policy*, 31, pp. 1035-1052.

Forman, Chris. 2002. The Corporate Digital Divide: Determinants of Internet Adoption. Mimeo. Carnegie Mellon University.

Forman, Chris, Avi Goldfarb, and Shane Greenstein. 2002. Digital Dispersion: An Industrial and Geographic Census of Commercial Internet Use. NBER Working Paper #9287.

Gaspar, Jess, and Glaeser, Edward. 1998, "Information Technology and the Future of Cities." *Journal of Urban Economics*, 43(1), pp. 136-156.

Goolsbee, Austan and Peter Klenow. 2002. Evidence on Learning and Network Externalities in the Diffusion of Home Computers. *Journal of Law and Economics* 45(2), pp. 317-344.

Gorman, Sean P., 2002, "Where are the Web Factories: The Urban bias of E-Business Location." Mimeo, Neoteric Media Inc., Arlington VA.

Greenstein, Shane, 2003. "The Economic Geography of Internet Infrastructure in the United States," in (eds) M. Caves, S. Majumdar, and I. Vogelsang, *The Handbook of Telecommunications Economics. Volume II.* Elsevier.

Harris, Richard, 1998, "The Internet as a GPT: Factor Market Implications," in E. Helpman (eds.), *General Purpose Technologies and Economic Growth*. Cambridge: MIT Press.

Henry, David, and Donald Dalton, 2002, "Information Technology Industries in the New Economy," Chapter III in Digital Economy 2002, Department of Commerce, at http://www.esa.doc.gov/reports.cfm.

Hitt, Lorin and Erik Brynjolfsson. 1997. Information Technology and Internal Firm Organization: An Exploratory Analysis *Journal of Management Information Systems* 14 (Summer): 1-101.

Hubbard, Tom. 2000. "The Demand for Monitoring Technologies: The Case of Trucking." *Quarterly Journal of Economics* 116 (May): 533-560.

Ireland, N. and Stoneman, P. 1986. Technological diffusion, expectations and welfare. Oxford Economic Papers 38, 283-304.

Kolko, Jed, 2000, "The Death of Cities? The Death of Distance? Evidence from the Geography of Commercial Internet Usage," In Ingo Vogelsang and Benjamin M. Compaine (eds), *The Internet Upheaval*. Cambridge, MA: MIT Press.

Kolko, Jed, 2002, "Silicon Mountains, Silicon Molehills, Geographic Concentration and Convergence of Internet Industries in the US," *Information Economics and Policy* 14(2), 211-232.

Krugman, Paul, 1991, *Geography and Trade*. Cambridge: MIT Press.

Marshall, Alfred. 1920. Principles of Economics. 8th edition. New York: Porcupine Press

Moss, Mitchell L., and Anthony M. Townsend, 1997. Tracking the net: using domain names to measure the growth of the Internet in US cities. *Journal of Urban Technology* 4(3): 47-60.

National Telecommunications Information Administration, 2000a, Falling Through the net: Toward Digital Inclusion. See http://www.ntia.doc.gov/reports.html.

---, 2000b. "Advanced Telecommunications in Rural America, The Challenge of Bringing Broadband Service to All Americans." See http://www.ntia.doc.gov/reports.html.

---, 1999, "Falling Through the Net: Defining the Digital Divide." http://www.ntia.doc.gov/reports.html.

---, 1998. "Falling Through the Net II: New Data on the Digital Divide." http://www.ntia.doc.gov/reports.html.

---, 1995. "Falling Through the Net: A Survey of the 'Have Nots' in Rural and Urban America." http://www.ntia.doc.gov/reports.html.

Noll, Roger, Dina Older-Aguilar, Gregory Rosston, and Richard Ross, 2001, "The Digital Divide: Definitions, Measurement, and Policy Issues," Paper presented at the American Economics Association Meetings, January 2002.

Price, Lee, with George McKittrick, 2002, "Setting the Stage: The New Economy Endures Despite Reduced IT Investment," in Chapter I, Digital Economy 2002, Department of Commerce, at http://www.esa.doc.gov/reports.cfm.

Rogers, Everett, 1995. *The Diffusion of Innovations.* Fourth Edition. New York: Free Press.

Sinai, Todd and Joel Waldfogel, 2001, “Geography and the Internet: Is the Internet a Substitute or a Complement for Cities?” Working Paper, Wharton School of Business, University of Pennsylvania, Philadelphia.

U.S. Department of Agriculture, 2001, Farm Computer Usage and Ownership Report, 07.30.01, http://usda.mannlib.cornell.edu/reports/nassr/other/computer/

United States Department of Commerce. 2002. “A Nation Online: How Americans are expanding their use of the Internet, Joint Report from the National Telecommunications and Information Administration and the Economics and Statistics Administration.

Zooks, Matthew, 2000a, “Internet Metrics: Using Hosts and Domain Counts to Map the Internet Globally,” *Telecommunications Policy,* 24, 6/7.

Zooks, Matthew, 2000b, “The Web of Production: the Economic Geography of Commercial Internet Content Production in the United States,” *Environment and Planning*, 32: 411-26.

Table 1

Predictions of Alternative Hypotheses

Hypothesis	Prediction
Global Village	$dNB/dx_i < 0$
Urban Density	$dNB/dx_i > 0$
General Purpose Technology	dNB/dx_i *for enhancement* > dNB/dx_i *for participation*
Industry Composition (IC)	$dNB/dx_i = 0$; $dNB/dz_i > 0$
Industry-Agglomeration Complements	$dNB/dz_i > 0$, $dNB/dx_i > 0$, and $d^2NB/ dx_i dz_i > 0$
Industry-Agglomeration Substitutes	$dNB/dz_i > 0$, $dNB/dx_i > 0$, and $d^2NB/ dx_i dz_i < 0$

x_i describes geographic conditions such as population size and density.

z_i describes the IT-intensity of an industry.

Table 2
National Internet Adoption Rates (in percentages)

	Weighted Average	Unweighted Average
Participation	88.6%	80.7%
Enhancement	12.6%	11.2%
Enhancement & Experimenting with Enhancement	23.2%	18.1%

Table 3
Average Adoption by Size of Metropolitan Statistical Area

Population	Average Participation	Standard Error	Average Enhancement	Standard Error	Number of Areas
Non-MSA	85.1%	0.1%	10.6%	0.2%	49
<250,000	75.5%	0.2%	9.9%	0.3%	143
250,000-1 million	84.9%	0.2%	11.2%	0.3%	116
> 1 million	90.4%	0.1%	14.7%	0.2%	57

Table 4a: Participation Among Metropolitan Statistical Areas with Over One Million People

Avg. Rank	City	Avg. Rate	Std. Err. Rate	Marg. Rank	Marg. Coef.	Std. Err. Coef.	Obs.	Population
1	San Francisco--Oakland--San Jose, CA	96.4%	0.4%	7	0 (base)	N/A	2135	7,039,362
2	Denver--Boulder--Greeley, CO	95.9%	0.7%	43	-0.067	0.027	940	2,581,506
3	Cleveland--Akron, OH	94.8%	0.6%	23	-0.038	0.021	1099	2,945,831
4	Seattle--Tacoma--Bremerton, WA	93.9%	0.5%	3	0.025	0.015	1012	3,554,760
5	Salt Lake City--Ogden, UT	93.5%	0.8%	6	0.007	0.019	535	1,333,914
6	San Antonio, TX	93.3%	0.8%	1	0.035	0.021	395	1,592,383
7	Providence--Fall River--Warwick, RI--MA	93.0%	1.2%	24	-0.038	0.032	290	1,188,613
8	Grand Rapids--Muskegon--Holland, MI	93.0%	0.7%	4	0.012	0.021	503	1,088,514
9	Minneapolis--St. Paul, MN--WI	92.7%	0.5%	10	-0.011	0.017	1411	2,968,806
10	Los Angeles--Riverside--Orange County, CA	92.5%	0.4%	38	-0.061	0.017	4099	16,373,645
11	Kansas City, MO--KS	92.2%	0.6%	21	-0.035	0.025	753	1,776,062
12	Austin--San Marcos, TX	92.1%	0.7%	2	0.033	0.026	344	1,249,763
13	Dallas--Fort Worth, TX	92.1%	0.5%	36	-0.058	0.019	1720	5,221,801
14	Portland--Salem, OR--WA	92.1%	0.6%	5	0.009	0.019	776	2,265,223
15	Houston--Galveston--Brazoria, TX	91.7%	0.6%	17	-0.032	0.018	1413	4,669,571
16	Phoenix--Mesa, AZ	91.6%	0.7%	13	-0.022	0.018	988	3,251,876
17	Raleigh--Durham--Chapel Hill, NC	91.6%	0.9%	9	-0.004	0.028	398	1,187,941
18	Columbus, OH	91.5%	0.9%	28	-0.048	0.025	574	1,540,157
19	Milwaukee--Racine, WI	91.5%	0.7%	14	-0.023	0.023	855	1,689,572
20	San Diego, CA	91.5%	0.7%	32	-0.053	0.023	738	2,813,833
21	Detroit—Ann Arbor--Flint, MI	91.4%	0.6%	42	-0.067	0.021	1621	5,456,428
22	Indianapolis, IN	91.3%	0.8%	22	-0.036	0.024	646	1,607,486
23	Greensboro--Winston-Salem--High Point, NC	91.1%	0.9%	18	-0.032	0.024	570	1,251,509
24	Atlanta, GA	90.9%	0.6%	40	-0.064	0.024	1426	4,112,198
25	Miami--Fort Lauderdale, FL	90.9%	0.7%	35	-0.057	0.020	1010	3,876,380
26	Charlotte--Gastonia--Rock Hill, NC—SC	90.7%	0.9%	46	-0.083	0.029	618	1,499,293
27	Boston—Worcester--Lawrence, MA--NH--ME--CT	90.6%	0.5%	12	-0.022	0.015	2231	5,819,100
28	Chicago--Gary--Kenosha, IL--IN—WI	90.5%	0.4%	27	-0.047	0.016	3431	9,157,540
29	New York—Northern NJ--Long Island, NY--NJ--CT--PA	90.5%	0.4%	30	-0.050	0.015	4775	21,199,865
30	Washington--Baltimore, DC--MD—VA--WV	90.4%	0.5%	20	-0.034	0.017	2222	7,608,070
31	Philadelphia-Wilmington-Atlantic City, PA—NJ--DE--MD	90.3%	0.5%	16	-0.031	0.017	1745	6,188,463
32	Rochester, NY	90.3%	1.0%	19	-0.033	0.028	373	1,098,201
33	Hartford, CT	90.2%	0.9%	15	-0.024	0.027	500	1,183,110
34	Oklahoma City, OK	90.2%	1.1%	8	-0.002	0.024	339	1,083,346
35	Memphis, TN--AR--MS	90.0%	1.0%	26	-0.045	0.027	437	1,135,614
36	Louisville, KY--IN	89.9%	1.0%	25	-0.044	0.027	448	1,025,598
37	Cincinnati--Hamilton, OH--KY—IN	89.7%	0.8%	41	-0.066	0.024	772	1,979,202
38	St. Louis, MO--IL	89.7%	0.7%	11	-0.020	0.020	936	2,603,607
39	Pittsburgh, PA	89.1%	0.8%	34	-0.056	0.023	727	2,358,695
40	Buffalo--Niagara Falls, NY	88.5%	1.1%	31	-0.051	0.030	393	1,170,111
41	Tampa--St. Petersburg--Clearwater, FL	88.4%	0.9%	33	-0.054	0.021	812	2,395,997
42	Jacksonville, FL	87.6%	1.3%	47	-0.094	0.032	373	1,100,491
43	Las Vegas, NV--AZ	87.2%	1.2%	48	-0.106	0.030	417	1,563,282
44	Sacramento--Yolo, CA	87.0%	1.2%	45	-0.070	0.034	427	1,796,857
45	Norfolk--Virginia Beach--Newport News, VA--NC	86.9%	1.2%	49	-0.110	0.032	374	1,569,541
46	New Orleans, LA	86.0%	1.1%	37	-0.06	0.031	386	1,337,726
47	West Palm Beach--Boca Raton, FL	85.9%	1.2%	29	-0.049	0.029	299	1,131,184
48	Orlando, FL	85.5%	1.0%	44	-0.067	0.025	622	1,644,561
49	Nashville, TN	84.6%	1.1%	39	-0.062	0.028	466	1,231,311

Table 4b: Enhancement Among Metropolitan Statistical Areas with Over One Million People

Avg. Rank	City	Avg. Rate	Std. Err. Rate	Marg. Rank	Marg. Coef.	Std. Err. Coef.	Obs.	Population
1	Denver—Boulder--Greeley, CO	18.3%	1.3%	3	0.016	0.015	940	2,581,506
2	San Francisco--Oakland--San Jose, CA	17.0%	0.9%	15	0 (base)	N/A	2135	7,039,362
3	Salt Lake City--Ogden, UT	16.7%	1.7%	6	0.013	0.017	535	1,333,914
4	Minneapolis--St. Paul, MN--WI	15.9%	1.0%	10	0.003	0.012	1411	2,968,806
5	Houston--Galveston--Brazoria, TX	15.7%	1.0%	11	0.003	0.012	1413	4,669,571
6	Atlanta, GA	15.4%	1.0%	26	-0.008	0.011	1426	4,112,198
7	Oklahoma City, OK	15.4%	2.0%	2	0.020	0.021	339	1,083,346
8	Dallas--Fort Worth, TX	15.3%	0.9%	19	-0.003	0.011	1720	5,221,801
9	San Antonio, TX	15.3%	1.9%	4	0.013	0.020	395	1,592,383
10	Portland--Salem, OR--WA	15.1%	1.3%	5	0.013	0.019	776	2,265,223
11	Providence--Fall River—Warwick, RI--MA	14.9%	2.2%	7	0.010	0.024	290	1,188,613
12	Austin--San Marcos, TX	14.7%	1.9%	27	-0.009	0.016	344	1,249,763
13	Cleveland--Akron, OH	14.7%	1.2%	21	-0.004	0.014	1099	2,945,831
14	Tampa--St. Petersburg—Clearwater, FL	14.6%	1.3%	8	0.009	0.015	812	2,395,997
15	Memphis, TN--AR--MS	14.5%	1.8%	14	0.002	0.021	437	1,135,614
16	Seattle--Tacoma--Bremerton, WA	14.5%	1.2%	16	-0.002	0.012	1012	3,554,760
17	Hartford, CT	14.4%	1.6%	25	-0.008	0.016	500	1,183,110
18	San Diego, CA	14.3%	1.3%	23	-0.005	0.014	738	2,813,833
19	Cincinnati--Hamilton, OH—KY--IN	14.2%	1.3%	24	-0.005	0.014	772	1,979,202
20	Washington--Baltimore, DC—MD—VA--WV	14.2%	0.8%	22	-0.005	0.010	2222	7,608,070
21	Chicago--Gary--Kenosha, IL—IN--WI	14.1%	0.7%	17	-0.002	0.009	3431	9,157,540
22	Rochester, NY	14.1%	1.9%	18	-0.003	0.018	373	1,098,201
23	Boston--Worcester--Lawrence, MA--NH--ME--CT	13.9%	0.8%	20	-0.004	0.011	2231	5,819,100
24	Detroit--Ann Arbor--Flint, MI	13.8%	0.9%	39	-0.016	0.010	1621	5,456,428
25	Kansas City, MO--KS	13.7%	1.3%	35	-0.014	0.013	753	1,776,062
26	Raleigh--Durham--Chapel Hill, NC	13.7%	1.7%	31	-0.012	0.017	398	1,187,941
27	Pittsburgh, PA	13.6%	1.3%	13	0.003	0.015	727	2,358,695
28	Indianapolis, IN	13.6%	1.4%	41	-0.019	0.014	646	1,607,486
29	Charlotte—Gastonia--Rock Hill, NC--SC	13.6%	1.5%	29	-0.010	0.014	618	1,499,293
30	West Palm Beach--Boca Raton, FL	13.6%	2.0%	12	0.003	0.025	299	1,131,184
31	Los Angeles--Riverside—Orange County, CA	13.5%	0.6%	37	-0.015	0.008	4099	16,373,645
32	Miami—Fort Lauderdale, FL	13.5%	1.1%	33	-0.013	0.011	1010	3,876,380
33	New York--Northern NJ--Long Island, NY-NJ-CT-PA	13.5%	0.6%	36	-0.015	0.008	4775	21,199,865
34	Philadelphia-Wilmington-Atlantic City, PA--NJ--DE--MD	13.3%	0.9%	44	-0.021	0.009	1745	6,188,463
35	St. Louis, MO--IL	13.2%	1.2%	28	-0.009	0.013	936	2,603,607
36	Louisville, KY--IN	13.2%	1.6%	9	0.006	0.024	448	1,025,598
37	Columbus, OH	13.0%	1.5%	30	-0.011	0.018	574	1,540,157
38	Buffalo—Niagara Falls, NY	12.9%	1.7%	42	-0.019	0.014	393	1,170,111
39	Phoenix—Mesa, AZ	12.4%	1.1%	34	-0.014	0.012	988	3,251,876
40	Greensboro—Winston-Salem—High Point, NC	12.2%	1.4%	43	-0.020	0.015	570	1,251,509
41	Grand Rapids--Muskegon—Holland, MI	12.0%	1.5%	47	-0.031	0.012	503	1,088,514
42	New Orleans, LA	11.9%	1.7%	40	-0.018	0.016	386	1,337,726
43	Milwaukee--Racine, WI	11.7%	1.2%	38	-0.016	0.014	855	1,689,572
44	Nashville, TN	11.7%	1.5%	32	-0.012	0.016	466	1,231,311
45	Jacksonville, FL	11.3%	1.7%	48	-0.034	0.014	373	1,100,491
46	Sacramento--Yolo, CA	11.8%	1.6%	1	0.041	0.050	427	1,796,857
47	Norfolk--Virginia Beach—Newport News, VA--NC	10.8%	1.7%	45	-0.021	0.017	374	1,569,541
48	Orlando, FL	10.5%	1.3%	46	-0.027	0.012	622	1,644,561
49	Las Vegas, NV--AZ	9.0%	1.4%	49	-0.043	0.012	417	1,563,282

Table 5
Population Variables
(Standard errors in parentheses)

		Participation				Enhancement			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A.	Small MSA	0.0095				0.0198			
Coefficients from (Weighted) Probit Regressions		(0.0285)				(0.0350)			
	Medium MSA	-0.0491				0.0449			
		(0.0227)*				(0.0265)+			
	Large MSA	-0.0262				0.0632			
		(0.0201)				(0.0228)**			
	MSA Population		-3.95e-09	1.36e-08			-8.80e-10	2.10e-08	
			(3.80e-09)	(1.02e-08)			(3.24e-09)	(1.15e-08)+	
	MSA Population Squared			-1.94e-15				-2.39e-15	
				(1.13e-15)+				(1.24e-15)+	
	Medium-Low Density				-0.0170				0.0275
					(0.0194)				(0.0224)
	Medium-High Density				-0.0282				0.0860
					(0.0200)				(0.0244)**
	High Density				-0.0177				0.0577
					(0.0224)				(0.0224)*
	Log Likelihood	-33470.6	-33472.1	-33469.3	-33473.5	-28694.7	-28696.9	-28693.1	-28688.2
	Pseudo R^2	0.2252	0.2252	0.2252	0.2251	0.0593	0.0592	0.0593	0.0595
		Participation				**Enhancement**			
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
B.	Small MSA	0.0021				0.0035			
Marginal Effects from (Weighted) Probit Regressions		(0.0064)				(0.0062)			
	Medium MSA	-0.011				0.008			
		(0.0052)*				(0.0048)+			
	Large MSA	-0.0058				0.0110			
		(0.0045)				(0.0039)**			
	MSA Population		-8.89e-10	3.06e-09			-1.54e-10	3.67e-09	
			(8.56e-10)	(2.30e-09)			(5.67e-10)	(2.02e-09)+	
	MSA Population Squared			-4.37e-16				-4.18e-16	
				(2.55e-16)+				(2.17e-16)+	
	Medium-Low Density				-0.00385				0.00485
					(0.00440)				(0.00399)
	Medium-High Density				-0.00639				0.0154
					(0.00456)				(0.00450)**
	High Density				-0.00400				0.0103
					(0.00508)				(0.00406)*

Notes:
standard errors are in parentheses.
(1) non-MSA is the base for these regressions
(2) & (3) Since no meaningful population data was available for non-MSA areas, we include a "rural area" dummy variable in each of these regressions. The population and density variables were interacted with (1-RURAL). Therefore the coefficients on the population variables do not include non-MSA areas.
(4) low density is the base for these regressions. One quarter of the observations fit into each density type.
+significant at 90% confidence level
*significant at 95% confidence level
**significant at 99% confidence level

Table 6
Average and Median Location Effects, by Type of Location

Type	N	Median Participation Marginal Effect	Average Participation Marginal Effect	Std Dev Participation Marginal Effect	Median Enhancement Marginal Effect	Average Enhancement Marginal Effect	Std Dev Enhancement Marginal Effect
Rural	49	-0.029	-0.0292	0.0486	-0.020	-0.0135	0.0274
Small MSA	130*	-0.0225	-0.0271	0.0772	-0.018	-0.00708	0.0495
Medium MSA	95	-0.046	-0.0535	0.0579	-0.012	-0.0111	0.0313
Large MSA	48	-0.0445	-0.0397	0.0324	-0.008	-0.00652	0.0150

*N=127 for enhancement because 3 small MSAs perfectly predicted non-adoption.

Table 7a
Population Variable Coefficients from (weighted) Probit Regressions,
Includes Multi-Establishment/Population Interactions
(Standard errors in parenthesis)

	Participation				Enhancement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Multi-est. dummy	-.1511	-0.1661	-0.1661	-0.1509	-0.0578	-0.0014	-0.0038	-0.0463
	(0.0339)**	(0.0211)**	(0.0210)**	(0.0289)**	(0.0404)	(0.0210)	(0.0212)	(0.0334)
Small MSA	0.0247				0.0013			
	(0.0430)				(0.0492)			
Medium MSA	-0.0571				0.0317			
	(0.0321)+				(0.0342)			
Large MSA	-0.0463				0.0134			
	(0.0279)+				(0.0284)			
Small MSA ×	-0.0267				0.0532			
Multi-est. dummy	(0.0570)				(0.0696)			
Medium MSA ×	0.0196				0.0436			
Multi-est. dummy	(0.0446)				(0.0538)			
Large MSA ×	0.0442				0.1234			
Multi-est. dummy	(0.0378)				(0.0447)**			
MSA Population		-1.27e-08*	-3.07e-09			-4.96e-09	2.07e-08	
		(5.16e-09)	(9.37e-09)			(4.08e-09)	(1.03e-08)*	
MSA Population			-1.09e-15				-2.92e-15	
Squared			(1.02e-15)				(1.13e-15)**	
MSA Population ×		1.86e-08**	1.82e-08**			1.45e-08	1.44e-08	
Multi-est. dummy		(6.38e-09)	(6.29e-09)			(5.91e-09)*	(6.01e-09)*	
Medium-Low				-0.0222				-0.0024
Density				(0.0280)				(0.0294)
Medium-High				-0.0212				0.0574
Density				(0.0286)				(0.0341)+
High Density				-0.0619				0.0059
				(0.0323)+				(0.0289)
Medium-low				0.0132				0.0760
density × Multi-est.				(0.0382)				(0.0450)+
Medium-high				-0.0112				0.0738
density × Multi-est.				(0.0386)				(0.0465)
High density ×				0.0961				0.1238
Multi-est.				(0.0417)*				(0.0435)**
Log Likelihood	-33467.9	-33463.5	-33462.5	-33465.8	-28686.8	-28695.9	-28689.2	-28681.9
Pseudo R^2	0.2253	0.2254	0.2254	0.2253	0.0596	0.0593	0.0595	0.0597

Notes:
All regressions include dummy variables for 3-digits NAICS, month that data was collected, and whether it was a multi-establishment firm. Employment and Employment squared were also included as controls. Population was measured at the MSA level.
(1) non-MSA is the base for these regressions
(2) & (3) Since no meaningful population data was available for non-MSA areas, we include a "rural area" dummy variable in each of these regressions. The population and density variables were interacted with (1-RURAL). Therefore the coefficients on the population variables do not include non-MSA areas.
(4) Low density is base for these regressions. One quarter of the observations fit into each density type.
+significant at 90% confidence level
*significant at 95% confidence level
**significant at 99% confidence level

Table 7b
Population Variable Marginal Effects from (weighted) probit regressions,
Includes multi-establishment effects
(Standard errors in parenthesis)

	Participation				Enhancement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Multi-est. dummy	-0.0343	-0.0377	-0.0377	-0.0342	-0.0101	-0.0002	-0.0007	-0.0081
	(0.0077)**	(0.0048) **	(0.0048) *	(0.0066)	(0.0070)	(0.0037)	(0.0037)	(0.0058)
Small MSA	0.0055				0.0002			
	(0.0095)				(0.0086)			
Medium MSA	-0.0131				0.0056			
	(0.0075)+				(0.0061)			
Large MSA	-0.0104				0.0023			
	(0.0062)+				(0.0050)			
Small MSA ×	-0.0061				0.0096			
Multi-est. dummy	(0.0132)				(0.0130)			
Medium MSA ×	0.0043				0.0078			
Multi-est. dummy	(0.0099)				(0.0098)			
Large MSA ×	0.0099				0.0224**			
Multi-est. dummy	(0.0083)				(0.0084)			
MSA Population		-2.85e-09	-6.91e-10			-8.68e-10	3.63e-09	
		(1.17e-09)*	(2.11e-09)			(7.15e-10)	(1.81e-09)*	
MSA Population			-2.44e-16				-5.12e-16	
Squared			(2.30e-16)				(1.98e-16)**	
MSA Population ×		4.19e-09	4.09e-09			2.53e-09	2.52e-09	
Multi-est. dummy		(1.44e-09)**	(1.42e-09) **			(1.03e-09)*	(1.05e-09)*	
Medium-Low				-0.0050				-0.0004
Density				(0.0064)				(0.0051)
Medium-High				-0.0048				0.0102
Density				(0.0065)				(0.0062)+
High Density				-0.0141				0.0010
				(0.0075)+				(0.0051)
Medium-low				0.0030				0.0138
density × Multi-est.				(0.0085)				(0.0085)
Medium-high				-0.0025				0.0134
density × Multi-est.				(0.0088)				(0.0087)
High density ×				0.0208				0.0229
Multi-est. dummy				(0.0087)*				(0.0085)**

Notes:
All regressions include dummy variables for 3-digits NAICS, month that data was collected, and whether it was a multi-establishment firm. Employment and Employment squared were also included as controls. Population was measured at the MSA level.
(1) non-MSA is the base for these regressions
(2) & (3) Since no meaningful population data was available for non-MSA areas, we include a "rural area" dummy variable in each of these regressions. The population and density variables were interacted with (1-RURAL). Therefore the coefficients on the population variables do not include non-MSA areas.
(4) Low density is base for these regressions. One quarter of the observations fit into each density type.
+significant at 90% confidence level
*significant at 95% confidence level
**significant at 99% confidence level

Table 8
Contribution of Industry and Location to Explaining Adoption Decisions

	Participation		Enhancement	
	Pseudo R^2	Log Likelihood	Pseudo R^2	Log Likelihood
Full model	0.2339	-33093.4	0.0672	-28443.4
No MSA Dummies	0.2251	-33475.0	0.0591	-28701.4
No NAICS dummies	0.1526	-36604.2	0.0347	-29434.6

Note: Cities defined by CMSA.

Table 9
Interaction of Industry and Location Effects

	A. Leading Internet Adopters (NAICS)				B. Top IT-using Industries (SIC)			
	Participation		Enhancement		Participation		Enhancement	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Small MSA	-0.0127	-0.0029	0.0085	0.0476	-0.0175	-0.00397	-0.00153	-0.000267
	(0.0302)	(0.0069)	(0.0062)	(0.0338)	(0.029)	(-0.0130)	(0.0405)	(0.00707)
Medium MSA	-0.0640	-0.0147	0.0013	0.0073	-0.0569	-0.0130	0.0279	0.00494
	(0.0241)**	(0.0056)**	(0.0047)	(0.0269)	(0.0237)*	(0.00554)*	(0.0291)	(0.00521)
Large MSA	-0.0372	-0.0083	0.0042	0.0243	-0.0409	-0.00917	0.0371	0.00646
	(0.0214)+	(0.0048)+	(0.0040)	(0.0228)	(0.0210)+	(0.00470)+	(0.0247)	(0.00430)
Top 25 NAICS3	0.8869	0.1512	0.0390	0.2072				
	(0.7270)	(0.0906)	(0.0908)	(0.4489)				
Small MSA*	0.2791	0.0539	-0.0121	-0.0727				
Top 25 NAICS3	(0.0864)**	(0.0140)**	(0.0169)	(0.1062)				
Medium MSA*	0.1618	0.0335	0.0397	0.2020				
Top 25 NAICS3	(0.0692)*	(0.0131)*	(0.0181)*	(0.0831)*				
Large MSA*	0.1205	0.0259	0.0382	0.1998				
Top 25 NAICS3	(0.0582)**	(0.0119)**	(0.0155)*	(0.0744)**				
IT intense SIC					-0.0739	-0.0169	-0.0672	-0.0115
					(0.0702)	(0.0163)	(0.0662)	(0.0112)
Small MSA*					0.1761	0.0361	0.0917	0.0170
IT intense SIC					(0.0927)+	(0.0171)+	(0.0833)	(0.0163)
Medium MSA*					0.0683	0.0149	0.0773	0.0141
IT intense SIC					(0.0707)	(0.0149)	(0.0677)	(0.0129)
Large MSA*					0.0996	0.0217	0.1022	0.0187
IT intense SIC					(0.0620)	(0.0130)	(0.0595)+	(0.0113)+
Log Likelihood	-33464.7	-33464.7	-28674.1	-28674.1	-33465.9	-33465.9	-28691.3	-28691.3
Pseudo R^2	0.2253	0.2253	0.0600	0.0600	0.2253	0.2253	0.0594	0.0594

Notes:
Standard errors are in parentheses. Non-MSA is the base for these regressions
+significant at 90% confidence level
*significant at 95% confidence level
**significant at 99% confidence level

Figure 1
Comparison by City Size of Marginal Effects for Participation

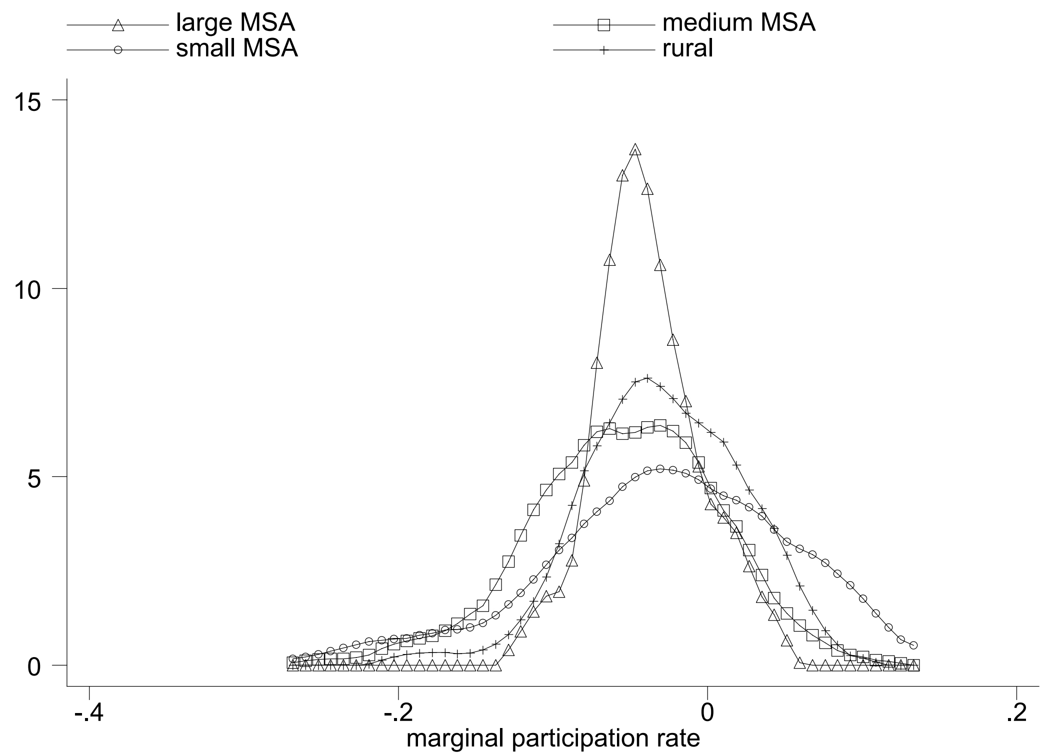

Figure 2
Comparison by City Size of Marginal Effects for Enhancement

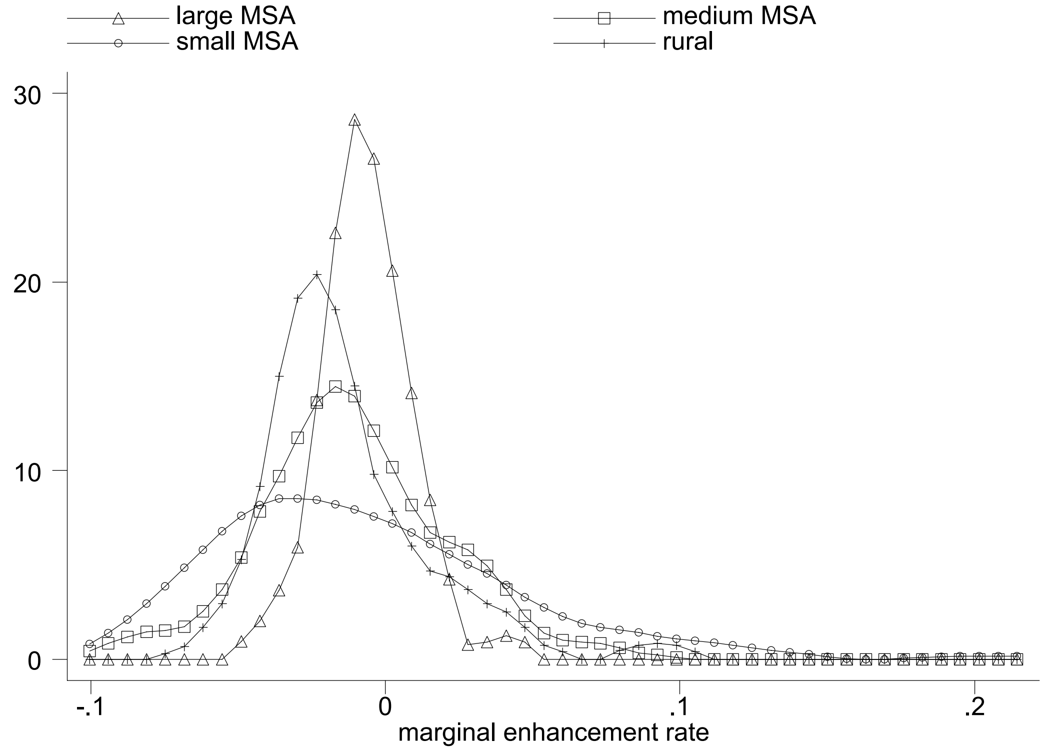

Figure 3
Differences in Industry Marginal Effects for Participation

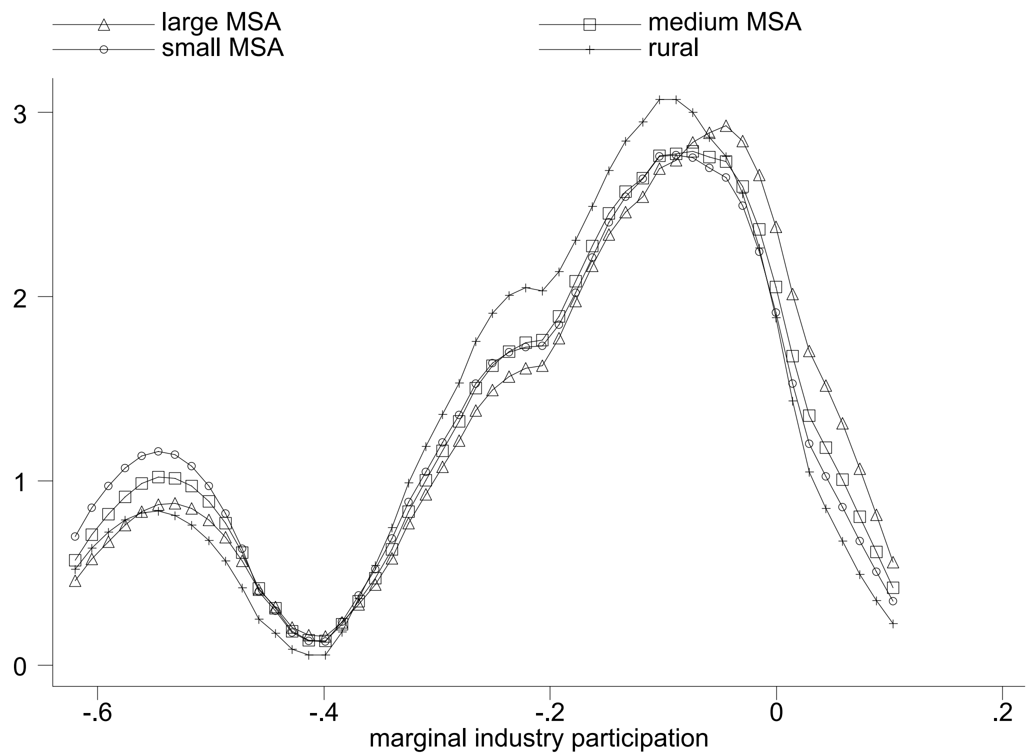

Figure 4
Differences in Industry Marginal Effects for Enhancement

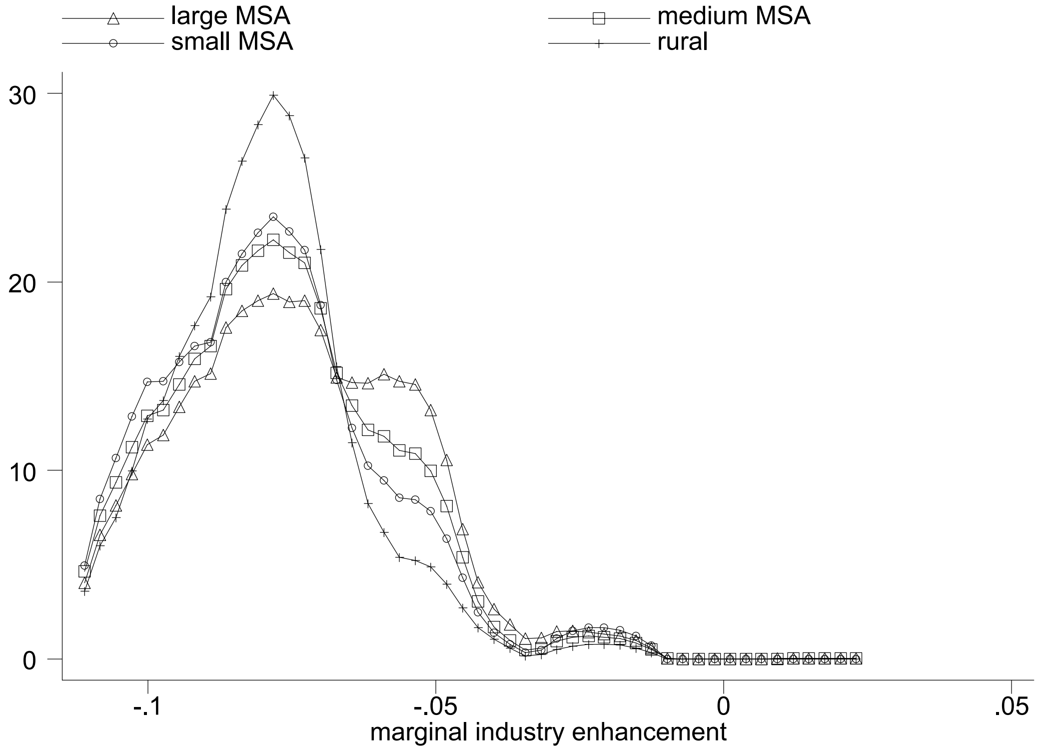

Table A1: Harte Hanks Sample Versus the Census of Business Establishments

	Sample	Census
# establishments with over 100 employees	86,879	168,372
% MSA	82.5%	86.7%
% CMSA	37.2%	42.5%
% >500 employees given have 100 employees	12.7%	10.6%
% Northeast	17.7%	19.6%
% Midwest	27.9%	25.5%
% South	34.8%	34.0%
% West	19.6%	21.0%
% Agriculture, Forestry, Fishing and Hunting (NAICS=11)	0.2%	0.1%
% Mining (NAICS=21)	0.6%	0.5%
% Utilities (NAICS =22)	0.8%	0.8%
% Construction (NAICS =23)	2.9%	4.1%
% manufacturing (NAICS =31, 32, 33)	27.9%	20.8%
% Wholesale Trade (NAICS =42)	6.0%	4.8%
% Retail Trade (NAICS =44, 45)	17.1%	14.7%
% Transportation & Warehousing (NAICS =48, 49)	2.9%	3.1%
% Media, Telecommunications and Data Processing (NAICS =51)	3.7%	3.7%
% Finance and Insurance (NAICS =52)	4.5%	4.6%
% Real Estate and Rental and Leasing (NAICS =53)	0.5%	1.0%
% Professional, Scientific and Technical Services (NAICS =54)	5.2%	5.0%
% Management of Companies and Enterprises (NAICS =55)	0.3%	3.2%
% Administrative and Support and Waste Management and Remediation Services (NAICS =56)	2.7%	10.2%
% Educational Services (NAICS =61)	0.01%	1.2%
% Health Care and Social Assistance (NAICS =62)	16.7%	12.8%
% Arts, Entertainment, and Recreation (NAICS =71)	1.6%	1.5%
% Accommodation and Food Services (NAICS =72)	5.5%	5.1%
% Other Services (except Public Administration) (NAICS =81)	0.9%	2.2%

Table A.2
Population Variable Marginal Effects from Probit Regressions in Table 5, Includes Percent Participation and Enhancement Adopters within Firm

	Model	Variable	Old Result	New Result
A. Weighted probits without IV	Add percentage other establishments adopting participation to column (1)	Small MSA	0.0021	0.0021
		Medium MSA	-0.0110*	-0.0112*
		Large MSA	-0.0058	-0.0063
		Pct shallow	N/A	0.2401**
	Add percentage other establishments adopting enhancement to column (5)	Small MSA	0.0035	0.0038
		Medium MSA	0.0080+	0.0081+
		Large MSA	0.0110**	0.0108**
		Pct deep	N/A	0.1026**
	Add percentage other establishments adopting participation to column (4)	Medium-Low Density	-0.0039	-0.0039
		Medium-High Density	-0.0064	-0.0069
		High Density	-0.0040	-0.0052
		Pct shallow	N/A	0.1637**
	Add percentage other establishments adopting enhancement to column (8)	Medium-Low Density	0.0049	0.0049
		Medium-High Density	0.0154**	0.0152**
		High Density	0.0103*	0.0099*
		Pct deep	N/A	0.1024**
B. Unweighted probits with IV#	Add percentage other establishments adopting participation to column (1) (instrument using average population)	Small MSA	0.0032	0.0025
		Medium MSA	-0.0072+	-0.0075+
		Large MSA	-0.0045	-0.0051
		Pct shallow	N/A	0.0193
	Add percentage other establishments adopting enhancement to column (5) (instrument using average population)	Small MSA	0.0095*	0.0097*
		Medium MSA	0.0077*	0.0078*
		Large MSA	0.0129**	0.0128**
		Pct shallow	N/A	0.0336
	Add percentage other establishments adopting participation to column (4) (instrument using average density)	Medium-Low Density	-0.0019	-0.0013
		Medium-High Density	-0.0012	-0.0010
		High Density	-0.0027	-0.0028
		Pct shallow	N/A	0.1538**
	Add percentage other establishments adopting enhancement to column (8) (instrument using average density)	Medium-Low Density	0.0044	0.0042
		Medium-High Density	0.0167**	0.0171**
		High Density	0.0110**	0.0114**
		Pct shallow	N/A	-0.1604

Notes:
Table compares results of probit regressions with and without variables measuring behavior of other establishments within the same firm.
[#] "Old" coefficients are different because probits are unweighted. Instruments are average population or density of locations other establishments in same firm
+significant at 90% confidence level
*significant at 95% confidence level
**significant at 99% confidence level

Table A.3
Population Variable Marginal Effects from Probit Regressions in Table 8, Includes Percent Participation and Enhancement Adopters within Firm

	Model	Variable	Old Result	New Result
A. Weighted probits without IV	Add percentage other establishments adopting participation to column (1)	Small MSA	0.0055	0.0042
		Medium MSA	-0.0131+	-0.0138+
		Large MSA	-0.0104+	-0.0111+
		Small MSA * Multi-est dummy	-0.0061	-0.0099
		Medium MSA * Multi-est dummy	0.0043	0.0054
		Large MSA * Multi-est dummy	0.0099	0.0098
		Multi-est dummy	-0.0343**	-0.1510**
		Pct shallow	N/A	0.1636**
	Add percentage other establishments adopting enhancement to column (5)	Small MSA	0.0002	0.0005
		Medium MSA	0.0056	0.0059
		Large MSA	0.0023	0.0029
		Small MSA * Multi-est dummy	0.0096	0.0096
		Medium MSA * Multi-est dummy	0.0078	0.0071
		Large MSA * Multi-est dummy	0.0224**	0.0205*
		Multi-est dummy	-0.0101	-0.0219**
		Pct deep	N/A	0.1015**
	Add percentage other establishments adopting participation to column (4)	Medium-Low Density	-0.0050	-0.0057
		Medium-High Density	-0.0048	-0.0058
		High Density	-0.0141+	-0.0145*
		Medium-Low Density * Multi-est dummy	0.0030	0.0042
		Medium-High Density * Multi-est dummy	-0.0025	-0.0016
		High Density * Multi-est dummy	0.0208*	0.0195*
		Multi-est dummy	-0.0342	-0.1505**
		Pct shallow	N/A	0.1634**
	Add percentage other establishments adopting enhancement to column (8)	Medium-Low Density	-0.0004	-0.0001
		Medium-High Density	0.0102+	0.0107+
		High Density	0.0010	0.0016
		Medium-Low Density * Multi-est dummy	0.0138	0.0131
		Medium-High Density * Multi-est dummy	0.0134	0.0117
		High Density * Multi-est dummy	0.0229**	0.0207*
		Multi-est dummy	-0.0081	-0.0199**
		Pct deep	N/A	0.1014**

B. Unweighted probits with IV#	Add percentage other establishments adopting participation to column (1) (instrument using average population)	Small MSA	0.0050	0.0041
		Medium MSA	-0.0076	-0.0081
		Large MSA	-0.0072	-0.0077+
		Small MSA * Multi-est dummy	-0.0032	-0.0032
		Medium MSA * Multi-est dummy	0.0011	0.0011
		Large MSA * Multi-est dummy	0.0056	0.0049
		Multi-est dummy	-0.0315***	-0.0311+
		Pct shallow	N/A	0.0150
	Add percentage other establishments adopting enhancement to column (5) (instrument using average population)	Small MSA	0.0065	0.0064
		Medium MSA	0.0029	0.0026
		Large MSA	0.0017	0.0013
		Small MSA * Multi-est dummy	0.0090	0.0091
		Medium MSA * Multi-est dummy	0.0137+	0.0140+
		Large MSA * Multi-est dummy	0.0288**	0.0299**
		Multi-est dummy	-0.0125*	-0.0037
		Pct shallow	N/A	-0.0904
	Add percentage other establishments adopting participation to column (4) (instrument using average density)	Medium-Low Density	-0.0016	-0.0021
		Medium-High Density	0.0023	0.0013
		High Density	-0.0113*	-0.0115*
		Medium-Low Density * Multi-est dummy	-0.0004	0.0018
		Medium-High Density * Multi-est dummy	-0.0065	-0.0042
		High Density * Multi-est dummy	0.0175**	0.0177**
		Multi-est dummy	-0.0315**	-0.1316**
		Pct shallow	N/A	0.1384**
	Add percentage other establishments adopting enhancement to column (8) (instrument using average density)	Medium-Low Density	-0.0017	-0.0024
		Medium-High Density	0.0052	0.0041
		High Density	0.0000	-0.0015
		Medium-Low Density * Multi-est dummy	0.0159*	0.0173**
		Medium-High Density * Multi-est dummy	0.0279**	0.0326**
		High Density * Multi-est dummy	0.0279**	0.0336**
		Multi-est dummy	-0.0113*	0.0156
		Pct shallow	N/A	-0.2599

Notes:
Table compares results of probit regressions with and without variables measuring behavior of other establishments within the same firm.
"Old" coefficients are different because probits are unweighted. Instruments are average population or density of locations other establishments in same firm
+significant at 90% confidence level
*significant at 95% confidence level
**significant at 99% confidence level