How Did Location Affect Adoption of the Commercial Internet? Global Village vs. Urban Leadership

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Abstract

We provide a framework and evidence to confront two contradictory yet common assertions: (1) new technology such as the Internet favors businesses in urban areas and (2) the Internet reduces the importance of distance for economic activity. Controlling for other factors, we show that participation in the Internet is more likely in rural areas than in urban areas. This is particularly true for technologies that involve communication across establishments. Nevertheless, talk of the dissolution of cities is premature. Frontier Internet technologies for communication within an establishment appear more often at establishments in urban areas, even with industry controls (JEL classification L63, L86, R0).

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1. INTRODUCTION

The emergence of the commercial Internet had a large and readily apparent impact on firm investment during the booming 1990s. From 1995 (when Internet technology became commercially available) to the end of 2000, stocks of information technology (IT) capital grew by 20% annually. A large fraction of this investment was affiliated with business applications and infrastructure using Internet-related technology. In 2000, total business investment in IT goods and services was $466 billion, almost triple the level for personal expenditure on similar goods.[1] Considerable evidence suggests that this half-decade's worth of investment had a large impact on U.S. firm performance and productivity.

In this study, we examine two contradictory yet common assertions about how such investment shaped geographic differences in economic outcomes. One stream of research argues that Internet technology requires infrastructure and support services, which are more readily available in urban settings. It forecasts that businesses in urban settings use Internet applications more frequently than similar firms in rural settings. It also argues that most of the productivity benefits from Internet investments accrued to urban businesses. A second stream of research argues that Internet technology reduces the importance of distance by decreasing coordination costs within firms and between firms. In particular, Internet technology dramatically reduces the costs of performing isolated economic activities in isolated areas, even when deployment costs are high. Both views have been supported by an extensive case study literature.

The difference centers on whether urban or rural business users faced lower or higher costs and benefits from the Internet. It is not a debate about what is *plausible*, since illustrative case studies and theoretical speculation support both outlooks. The open empirical question concerns the generality of illustrative cases, whether they are isolated examples or are representative of broad patterns. We address this open topic by empirically examining the marginal contribution of location to a variety of Internet adoption decisions.

We analyze a cross-section of potential adopters of Internet technology in business. We analyze four business purposes for the Internet – *participation* and *enhancement* business computing applications, and within these, technologies designed for communication *within* establishments and *across* establishments. While controlling for other factors, we estimate the probability that an economic establishment adopts the Internet for each of these four purposes. Specifically, *participation* refers to adoption of simple applications, a minimal requirement for coordinating geographically isolated locations. It includes basic communications such as email use, browsing, and passive document sharing. *Enhancement* refers to adoption of complex applications requiring technical support and third party servicing. It includes investment in frontier applications such as "e-commerce" or "e-business," as well as

[1] For 2000, estimated personal consumption of IT goods and services was $165 billion. See Henry and Dalton [20].

investment in intermediate goods used to support such investments. Participation is less costly than enhancement and requires less sophisticated local support than enhancement. Furthermore, within-establishment Internet (WEI) technologies help coordinate activities within an establishment, while cross-establishment Internet (CEI) technologies help coordinate geographically isolated activities between establishments. All else being equal, cross-establishment activities – for either purposes of participation or enhancement – yield larger gross benefits to firms located in rural locations than to those in urban locations, whereas the benefits to within-establishment activities do not vary with location.

In our framework, contrasting assertions about geography and the Internet imply different forecasts about the marginal contribution of location to the probability of adopting different business applications. Our first hypothesis, which we label *urban leadership*, predicts that firms in dense locations adopt the Internet more quickly because such locations allow for the pooling of resources. Adoption costs are therefore lower. This effect may be exaggerated because IT-friendly firms historically locate in cities in order to take advantage of lower costs, though perhaps not in anticipation of the Internet specifically. In contrast, the *global village* hypothesis predicts that firms in small cities and rural areas adopt the Internet more quickly than urban firms because the marginal returns from the use of the communications capabilities of the Internet are higher in remote locations.

Addressing our research goals requires detailed data about the largest investors in IT in the United States. We examine decision making at business establishments, and we use a sampling definition similar to Census surveys of businesses at specific addresses. Approximately two-thirds of the U.S. workforce is employed in the type of establishments studied. We analyze Internet adoption at 86,879 establishments that have over 100 employees; this sample comprises roughly one-half of U.S. establishments of such size. It consists of established firms rather than start-ups, which allows us to treat establishment location as exogenous. The data come from a survey updated to the end of 2000 and undertaken by Harte Hanks Market Intelligence (hereafter Harte Hanks), a commercial market research firm. The strength of this data is its breadth; we provide the first-ever census of Internet technology adoption. Its principal weakness is the absence of reliable estimates about capital stocks. This forces us to use discrete measures of Internet technology adoption rather than (more ideal) investment dollar values.

Our research supports three central findings:

1. Global village is supported when the Internet is adopted for *participation* purposes. In other words, controlling for industry, participation decreases with the size and density of a city; however, the magnitude of location's impact is small. When this result is broken down into WEI and CEI technologies, we find this result is strongest in cross-establishment (CEI) technologies.
2. We reach the opposite conclusion for *enhancement*. Even with industry controls, urban leadership is supported: the probability that an establishment will adopt enhancement applications increases with the population of a location. When this result is broken down into WEI and CEI

technologies, we find that urban leadership is supported by within-establishment (WEI) technologies only.

3. The findings rely on estimates of marginal effects. Average adoption rates show higher adoption rates for urban areas in both participation and enhancement. The difference between marginal and average rates is largely explained by differences in industry composition across major cities. More IT-intensive industries tend to cluster in urban areas. The effects of urban leadership and industry composition interact in a complementary way for enhancement applications. This interaction could exacerbate agglomeration in use.

Overall, our findings reconcile the two seemingly contradictory assertions found in the literature. Our evidence suggests that the Internet reduces the importance of distance. This evidence is strongest for participation technologies that involve cross-establishment communications (CEI) that reduce the costs of distance. Our evidence is also consistent with urban leadership for enhancement technology, especially for WEI enhancement. None of our results contradict the claim that dense urban areas provide locals with many advantages. Rather, the evidence is consistent with this claim *and* with the view that some Internet technology applications had great appeal to businesses in less dense settings. In addition, we find considerable variation in the benefits to Internet adoption across locations. Such variation may ultimately influence productivity differences across regions and thereby reshape long-run comparative advantage.

While our evidence covers only the earliest period of use of this technology, the foundations for our empirical framework arise from general economic theories of technology adoption in IT. Hence, we believe that global village and urban leadership will continue to influence the economic geography of the costs and benefits of IT investment.

1.1 Previous Literature

Although an extensive econometric and case study literature has examined the productivity-enhancing benefits of IT and the Internet (e.g., Oliner and Sichel [26]; Stiroh [28]; Bresnahan, Brynjolfsson and Hitt [4]), there has been comparatively little work examining geographic variation in Internet usage. We follow a long line of economic analysis (e.g., Griliches [19]) that employs geographic variance in the use of a well-defined innovation as a window into the factors shaping an innovation's costs and benefits. Our study builds on earlier findings (Forman, Goldfarb and Greenstein [13, 14]) that geographic patterns of Internet adoption in business differ substantially from the patterns uncovered in any existing research on early adopters. This includes research on Internet adoption by households, technology adoption by businesses, and general infrastructure deployment. *On average,* businesses located in urban areas employ Internet technology more than those in less dense locations, a pattern that contradicts the global village hypothesis, as predicted by prior authors (see, e.g., Cairncross [5]).

In this study we decompose these adoption rates into their *marginal* determinants. Unlike other empirical studies in this vein, we do not consider the determinants of long-run equilibrium, that is, where firms relocate after technology markets develop (e.g., Beardsell and Henderson [1]; Kolko [23]; Charlot and Duranton [8]; Fitoussi [11]). Rather, we follow the accounts of how this technology diffused and examine the short-run reaction of establishments to something new. We ask whether an otherwise similar establishment in a different location displays different adoption behavior.

Kolko's [22] study is the most similar to our empirical question of how location affects Internet practice. He uses domain name registrations in the context of a central city/periphery model and finds that users in cities of medium size and above have registration patterns consistent with those areas benefiting disproportionately from the Internet. We also examine businesses' adoption of certain processes in cities of varying size and location. Some of our results can also be interpreted in this central city/periphery framework rather than the urban/rural one that we emphasize; however, Kolko has only one measure of Internet activity, registrations, so he does not develop the implications for different types of communications and purposes, as we do here.

Similar in spirit, but more distant in its context, is Sinai and Waldfogel's [27] study. While they examine household behavior for evidence that Internet content is either a substitute or a complement to content found locally, our focus is on adoption by business establishments. Moreover, our decomposition of the geographic variation of Internet use into industry- and location-specific factors enables us to test a different set of hypotheses.

Our hypotheses about the Internet build on the theory of General Purpose Technology, or GPT (Bresnahan and Trajtenberg [3]). The GPT framework motivates our distinction between participation and enhancement, and our emphasis on the importance of local market-based support for diffusion. Further, our examination of differences in the adoption of participation and enhancement relies on co-invention theory (Bresnahan and Greenstein [2]) that describes how firms must often make considerable investments to adapt GPTs to idiosyncratic business needs.

Finally, our analysis and findings contrast strongly with the prevailing analysis inspired by literature on the digital divide (e.g., National Telecommunications Information Administration [25]). In particular, urban leadership has received considerable exposure (e.g., Zook [31]; Castells[6]; Moss and Townsend [24]; Greenstein [18]). Like previous studies, we 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 is concentrated in a small number of places. Moreover, we offer very different explanations about the factors shaping geographic variation in use.

2. TESTABLE HYPOTHESES OF A TECHNOLOGY ADOPTION MODEL

In this section we develop a model of Internet technology adoption. This model frames competing hypotheses for the observed geographic variance in Internet adoption. We posit that establishment *i* will adopt Internet technology by time *t* if

$$(1) \qquad NB(x_i,z_i,t) \equiv B(x_i,z_i,t) - C(x_i,z_i,t) > 0,$$

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,[2] while z_i describes industry characteristics that may affect a firm's decision to adopt Internet technology.

Our data come from one cross-section. Since adoption of the Internet is rarely reversed, we are comfortable suppressing the time dimension in our model. Under the standard "probit model" of diffusion (e.g., David [10]; Karshenas and Stoneman [21]), adoption costs decline over time for all potential adopters. Therefore the difference between adoption and non-adoption reveals the threshold between those with high and low valuations from use.[3] This simple model frames our predictions. For reference, see Table 1, where we list each of the open questions addressed and the associated testable hypotheses.

2.1 Global Village Versus Urban Leadership

The first and second hypotheses offer contrasting arguments about how adoption costs increase or decrease as population size and density increase.

Urban leadership argues that these costs decrease faster than the benefits decrease ($dNB/dx_i > 0$). The relationship holds more strongly if IT-friendly firms have presorted into urban areas.[4] Since most standard economic theory points towards the predictions of urban leadership, it is our null hypothesis.

The contrasting hypothesis, which we label global village, argues that establishments in rural or small urban areas derive the most benefit from communication technologies. Internet technology enables them to overcome diseconomies of small local size or substitute for the disadvantages associated with a remote location. More precisely, while all business establishments benefit from an increase in capabilities, the global village hypothesis argues that gross adoption benefits (1) decrease as population size and density increase (i.e., $dB/dx_i < 0$, where x_i is population size or density) and (2) decrease more rapidly

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[2] From this point forward, Metropolitan Statistical Areas (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*. In addition, when two or more MSAs are part of the same urban environment, the Census combines them into CMSAs, or Consolidated Metropolitan Statistical Areas. For example the Dallas-Fort Worth CMSA contains both Dallas and Forth Worth.

[3] 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.*

[4] As is well known, these explanations cannot be disentangled without detailed data on adoption over several generations of IT and relocation in response. This disentangling is not essential to our empirical goals. Each is a special case of urban leadership.

than do costs. Together, net benefits from adoption decline as population size and density increase ($dNB/dx_i \leq 0$). The global village hypothesis predicts that adoption of the Internet will be more common among establishments in rural areas than in urban areas, all other things being equal. To our knowledge, the global village hypothesis has not been directly tested and has not had much empirical verification.[5]

An alternative formulation, advocated by Gaspar and Glaser [17], is that electronic communication alters the marginal returns and frequency of face-to-face meetings in dense urban settings. There are three reasons why we de-emphasize this framework. First, we observe short run reactions to Internet technology, not any further economic adjustments, such as capital investments, relocation, and new firm entry, which are all relevant to Gaspar and Glaser's framework. Second, we are unable to directly measure change in face-to-face meetings from Internet investments. Third, it is not clear how much of the investment in Internet technology maps into this framework.[6]

2.2 Predictions of Global Village and Urban Leadership

This subsection examines the implications of global village and urban leadership on the importance of locations across technologies.

Participation and Enhancement: The contrast between participation and enhancement is informative about the adaptation costs necessary to adopt new IT (Bresnahan and Trajtenberg [3]). Adaptation costs are relevant to the adoption decision for enhancement and negligible for participation. If population density affects gross benefits for participation and enhancement in a similar way, then population density will affect net benefits more for participation than for enhancement.

WEI and CEI: WEI investments involve use of the Internet's TCP/IP (Transmission Control Protocol/Internet Protocol) for communication that remains within the boundaries of the establishment. CEI technologies represent Internet investments that involve communication between establishments within the value chain or between an establishment and its end consumers. If global village hypothesis holds, then gross benefits will vary by location for CEI technologies but will vary negligibly for WEI technologies. As a result, changes in location size and density will primarily influence costs (and not benefits) for WEI technologies ($dNB/dx_i \approx -dC/dx_i$). On the other hand, such changes will influence both costs and benefits of CEI technology adoption ($dNB/dx_i = dB/dx_i - dC/dx_i$). Therefore the net benefits of adoption are increasing faster in location size for WEI than for CEI (i.e., dNB/dx_i *WEI* $>$ dNB/dx_i *for CEI* since $dB/dx_i < 0$ and $dC/dx_i < 0$). This suggests that any results supporting global village will be especially strong for CEI technologies and any results supporting urban leadership will be especially strong for WEI technologies.

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[5] Forman [12] controls for urban/rural differences among a smaller sample of the Harte Hanks data using adoption data from an earlier period (1998).

[6] For example, one common Internet technology is the transmission of production data among establishments in different locations. This neither substitutes for nor complements face-to-face meetings.

2.3 Industry Composition

Establishments from the same industry tend to cluster in large areas to take advantage of thicker industry-specific labor markets and other shared local resources. As a result, differences in the average rate of Internet adoption across locations can be partially explained by the prior spatial distribution of industries. This implies two hypotheses. First, that IT-intensive industries concentrate in larger areas (i.e., $dNB/dz_i > 0$, corr(x_i, z_i) > 0). Second, that concentration of IT-intensive industries will explain geographic variation in participation and enhancement; that is, the rate with which the net benefits of adoption are increasing in size will be lower with industry composition controls ($dNB/dx_i > dNB/dx_i(.|z_i)$).

The separate impacts of industry and location may be different from their combined impact. In particular, IT-intensive industries may complement urban leadership. IT-intensive industries may be especially able to benefit from the rich resources available in cities ($d^2NB/ dx_i dz_i > 0$). This idea has received considerable exposure in the literature on the digital divide.

Alternatively, IT-intensive industries may be substitutes for urban leadership. Concentration of advanced industries may increase prices for local services. This idea has been discussed as a theoretical possibility (e.g., Gaspar and Glaeser [17]) but has seen little empirical verification.[7]

3. DATA AND METHOD

The data we use for this study come from the Harte Hanks Market Intelligence CI Technology database (hereafter CI database).[8] 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 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.

We focus on establishments as the unit of analysis for three reasons. First, the actions of establishments will reflect local factors better than individual workers (who are mobile) or organizations (that are in multiple locations). Second, previous studies of the organizational use of IT demonstrate that most co-invention expenses are incurred at a level wider than an individual. Third, and related, productivity advances occur across a wide array of interdependent processes at an establishment, even at those establishments where the Internet is not used widely.

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[7] One exception is Kolko [23], who examines agglomeration in the location decisions of IT-intensive firms.
[8] This section provides an overview. For more detail, see Forman, Goldfarb and Greenstein [12, 15].

Our sample from the CI database contains all commercial establishments with over 100 employees, 115,671 establishments in all; [9] and Harte Hanks provides one observation per establishment. We use the 86,879 clean observations with complete data generated between June 1998 and December 2000. We adopt a strategy of utilizing as many observations as possible because we need many observations for thinly populated areas. This necessitates routine adjustments of the data for the timing and type of the survey given by Harte Hanks. 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 only discrete choices: whether or not the establishment chooses participation and whether or not it chooses 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 establishment j of adopting the Internet is

$$(2) \qquad y_j=\alpha x_j+\beta I_j+\gamma S_j+\delta F_j+\varepsilon_j \,,$$

where x_j is a vector of population density measures, I_j is a vector of industry dummies, S_j is a vector of survey type and timing dummies,[10] and F_j is a vector of establishment characteristics such as employment and whether it is part of a multi-establishment firm. We assume the error terms of each establishment ε_j are normally distributed and independent across MSAs but potentially correlated within MSAs, and estimate a probit model with robust standard errors that are clustered by MSA.

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. 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. We then weight observations using Census County Business Patterns data to obtain a representative sample. We do this to illustrate the extent of overall variation in average adoption propensity. This exercise is valuable because it represents the most comprehensive survey of commercial Internet use across manufacturing and service industries to date.[11] Moreover, it provides a means of benchmarking our results against those in the prevailing literature on the digital divide, which focuses on average rates of adoption across locations (e.g., National Telecommunications Information Administration [25]). The variables for population density (x) and establishment characteristics (F) are replaced by location-specific dummies in this specification.

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[9] Previous studies (Charles, Ivis and Leduc [7]; Census [29]) 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.

[10] Harte Hanks used two surveys. One asked for more details on IT use than the other. We interact the long survey dummy variable with time. See Forman, Goldfarb and Greenstein [13] for more detail.

Our second and core purpose is to test competing hypotheses. We analyze the marginal contribution of different location-specific factors that shape adoption decisions at the establishment, and compare how this marginal contribution varies across technologies. We report marginal effects from a variety of different specifications, where model in Equation 2 is our base case. The coefficients are weighted to give a representative sample. (We subsequently display these results in Tables 5 through 9 and Figures 1 through 4). Two econometric assumptions underlie the estimates of marginal effects, namely, exogenous location and no simultaneity bias.

Exogenous Location: We examine short-run marginal effects of industry and location variables on the decision to invest in Internet technology. We assume that the location of an establishment is exogenous to the decision to adopt Internet technology. We argue that this assumption is supported by the (ex-ante) unexpected rapid diffusion of the Internet, as well as by a regression on a subset of the sample.

As noted in many contemporary accounts, 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. In this study we observe short-run adoption decisions five years into the diffusion of the commercial Internet, before medium and large establishments had time to relocate. We partially test this assumption by comparing results between our entire sample of establishments and a special sub-sample of establishments that (we are certain) fixed their locations prior to 1995 when the commercial Internet became available to most businesses. Since we find that the key estimates do not differ between these two samples, we infer that the potential endogeneity of establishment locations is not likely to alter our inferences about the influence of location on adoption of Internet technology.

The urban leadership hypothesis allows for the possibility that technology-friendly, though not necessarily Internet-friendly, establishments located in urban areas prior to its diffusion. Because we control for features of an establishment, this is a statement about whether our econometric model may contain omitted variables that influence the benefits of Internet adoption and which are correlated with prior location choice. This suggests unobservable previous choices favor the null hypothesis, stacking the deck in its favor. When we find in favor of the null, it clouds the interpretation—but not when we find against the null. We are comfortable with this asymmetric interpretive ambiguity, since it strengthens the surprise of finding against the null.

No Simultaneity Bias: Our base econometric specification assumes that the adoption decision of one establishment is independent of every other establishment's adoption decision, including other establishments in the same firm. This assumption is questionable for multi-establishment firms in which a central executive decision maker (e.g., a CIO) coordinates the choice to adopt or not adopt for each establishment under his domain. Adoption decisions at establishments from the same organization could

[11] Census [29] includes a larger sample of commercial Internet use but is confined to manufacturing firms.

be either substitutes or complements for one another. While understanding that this relationship is of independent interest, we instead focus on the relationship between location and adoption. We address these simultaneity concerns directly by including as instruments the decisions of related establishments at other locations in the reduced form regression described in equation (2), then measuring whether this alters the estimate of the coefficient on location. We find that the influence of location on adoption of Internet technology is robust to introducing simultaneity into the estimation.

3.2. Identifying Margins of Investment

As a GPT, Internet technology is employed in many different uses and applications. Our data include at least twenty different types of Internet technology, from basic access to software for Internet based-based Enterprise Resource Planning (ERP) business application software. Moreover, there are considerable differences in the applications used across establishments.

Identifying participation was more straightforward than identifying enhancement. We define participation by an establishment that has basic Internet access or has made any type of frontier investment.[12] The establishment survey provides plenty of information about these activities.

In contrast, enhancement activity is less transparent in the survey. We look for indications that an establishment has made investments that involved frontier technologies or substantial co-invention. Most often, these technologies involved inter-establishment communication and/or substantial changes to business processes. We identify enhancement from the presence of substantial investments in e-commerce or e-business applications. The threshold for defining *substantial* is necessarily arbitrary within a range.[13] To be clear, the investments we consider go beyond the downstream interactions with consumers that are traditionally thought of as retail e-commerce. They often involve upstream communication with suppliers, and/or new methods for organizing production, procurement, and sales practices. We look for commitment to two or more of the following projects: Internet-based ERP or Internet-based applications in customer service, education, extranet, publications, purchasing or technical support.[14]

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[12] 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 Internet-enabled 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 the Internet's TCP/IP protocols; (5) indicate there are Internet users or Internet developers on site; or (6) outsource some Internet activities. We looked for two or more activities to guard against "false positives." The vast majority of positive responses involved use of more than one of these criteria.

[13] We tested a number of slightly different definitions and did not find any significant changes to our findings.

[14] 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, common gateway interface (CGI), Perl, Visual Basic (VB) Script, or the extensible markup language (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, ERP, web development, or web server; (5) the establishment has an Internet server that is a UNIX workstation or server, mainframe, or minicomputer, or has five or more PC servers, or has Internet storage greater than twenty gigabytes; (6) the establishment answers three or more questions related to

We identified WEI and CEI technologies for both participation and enhancement. Within participation, WEI investments involve activities most commonly associated with the term "intranet," such as internal web pages and Internet-based networking. WEI enhancement investment involves the use of Internet protocols in the input and output of data to and from business applications software. Examples include business applications software that uses the Internet's TCP/IP protocols such as ERP or customer relationship management (CRM), or software used in business functions such as production, manufacturing, and accounting.

CEI participation technologies primarily involve basic access to the Internet, and enable activities such as passive web browsing or manual downloads of static data. CEI enhancement technologies involve advanced communications that permit, for example, commercial transactions between establishments within the value chain, as well as between establishments and end-consumers.

Our identification strategy is straightforward. By construction, every establishment that invests in enhancement also invests in participation, so differences in the adoption patterns across the two technologies are identified from establishments that invest in participation but not in enhancement. In practice, the vast majority of establishments invest in either CEI technologies or both WEI and CEI. In comparing CEI to WEI, identification is obtained primarily from establishments that have CEI but not WEI investments.

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 North American Industry Classification System (NAICS) code in each location.[15] 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

$$\frac{Total\ \#\ of\ census\ establishments\ in\ location-NAICS}{Total\ \#\ of\ census\ establishments\ in\ location}\cdot\frac{Total\ \#\ of\ establishments\ in\ our\ data\ in\ location}{Total\ \#\ of\ establishments\ in\ our\ data\ in\ location-NAICS} \tag{3}$$

Thus, if our data undersamples a given two-digit NAICS at a location relative to the Census then each observation in that NAICS-location is given more importance.

In Table 2, we present average rates for participation and enhancement for the United States. Participation by establishments within the sample is at 80.7% (see Unweighted Average in Table 2). The sample underrepresents adopters. Our estimate of the economy-wide distribution, using the true

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 [13].

[15] 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. The results are robust to weighting by firms with more than 100 employees in the Census and those with more than 25 employees.

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

There is considerable variation across locations in the average propensity to adopt Internet technologies. Table 3 shows participation and enhancement rates by Metropolitan Statistical Area (MSA) size in the United States. In previous work (Forman, Goldfarb and Greenstein [14], [16]), we contrasted our findings 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.

On the surface, this evidence supports urban leadership. We see that large MSAs have very high participation rates, averaging 90.4%. Participation rates in medium-sized MSAs and rural areas are lower at 84.9% and 85.1%, respectively. In small MSAs the participation rates are even lower, 75.5% on average. The disparities in enhancement adoption rates are even greater. 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. These averages suggest that urban leadership may hold. Differences between this table and the marginal effects (shown in the next section) are explained by differences in industry composition across locations.

There is also variance in adoption propensity within the subset of large MSAs. In Table 4, we list the participation and enhancement estimates for MSAs with over one million people, in order of highest to lowest enhancement adoption rates.[16] We list the standard errors and number of observations to identify the degree of statistical confidence in the estimates.

Participation is high in major urban locations. Virtually all establishments in the major urban areas are participating. Of the forty-nine MSAs, thirty-five are above 90%. All but five are within a 95% confidence interval of 90%. Nevertheless there are large differences between MSAs at the extremes. The top ten MSAs that adopted enhancement include a set of areas that partially overlaps with the top ten MSAs for participation. (Five of the top ten are also in the top ten for participation.) Again, the differences between the lowest adopting areas and the highest adopting areas are substantial. We next explore some potential causes for this variation.

[16] In Table 4, we present the CMSA results rather than the individual MSA results when an MSA is part of a CMSA.

5. THE MARGINAL IMPACT OF LOCATION ON INTERNET ADOPTION

This section presents the marginal effects of location on Internet adoption. We compare these marginal effects across participation/enhancement and WEI/CEI technologies. We summarize the main findings in Table 10, which is organized around the hypotheses listed in Table 1.

In this section, we present estimates of Equation 2 where observations are weighted 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/(two-digit) 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. We estimate probit regressions with robust standard errors that are clustered by MSA.

Part A of Table 5 presents the coefficients of the probit regressions. Part B presents the marginal effects. All probit regressions include dummy variables for three-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. Because prior studies suggest a correlation between establishment size and new technology adoption, we included employment and employment squared as controls. Population was measured at the MSA level and density at the county level. For columns 1 and 4, we use rural areas for the base. For columns 2 and 5, we include a "rural area" dummy for rural areas, since no meaningful population figures exist for these areas. In Columns 3 and 6 we include population density for all urban and rural areas by using low-density areas as the base. [17]

5.1 The Marginal Impact of Location

Table 5 shows no support for the urban leadership hypothesis in participation. Controlling for industry and firm characteristics, we show that location size and population density have a small negative impact on the decision to adopt at the participation level. The effects of location size and density support the global village hypothesis, but the impact of geography is of limited economic significance. In Column 1 we show that medium and large MSAs are 0.6% to 1.1% less likely to have adopted participation by the end of 2000. These estimates are statistically significant, but 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 the log of population in urban areas. Increases in population size do not increase the probability of participation. While not statistically significant, the coefficient suggests a possible decrease in the probability of participation. In Column 3 we include dummies for population density. This alternative specification provides very similar results.

[17] While population is measured at the MSA level, density is measured at the county level because it allows us to measure density in non-MSA areas. This consideration is not relevant for population.

In contrast to participation, the effects of population size and density on enhancement support urban leadership. In Column 4 we show that establishments in medium and large MSAs adopt enhancement at a rate 0.8% to 1.1% higher than rural areas. In Column 6 we show that establishments in medium-high and high density MSAs adopt enhancement at a rate 1.0% to 1.5% more than low density areas. All of these effects are statistically significant. They are economically significant in light of the average enhancement rates of 12.6%.

Together these results support GPT theory: the probability that an establishment adopts the Internet for enhancement increases faster with density than does the similar probability for participation. To statistically test this hypothesis, we estimated bivariate probit models of the decision to adopt participation and enhancement and examined whether the coefficient estimates were statistically different across the two margins of investment.[18] These models showed that our medium and large MSA estimates for participation are smaller than those for enhancement at the 1 percent level. Moreover, the difference between large and small MSA coefficients is smaller for participation than enhancement at the 10 percent level. We interpret this as evidence that applications more dependent on third-party support and complementary services are most costly to deploy in less dense locations.

Variance in the role of location varies by city size. In Figures 1 and 2 we graph the marginal effect of location. To create these figures, we divide locations into four types: large MSAs, medium MSAs, small MSAs, and statewide rural (non-MSA) regions. We re-estimated equation (2) for each of these four types using a separate dummy for each of the 366 individual locations rather than the four population size dummies used in our baseline specification. We compute the marginal effect of each location (e.g., the Hartford, CT MSA) on the probability of adoption, and then plot the kernel density estimates of the these marginal effects. Figure 1 plots these estimates for participation, and figure 2 does the same for enhancement. 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 slightly below any of the three other classes of geographic area. Although the distributions of each MSA size are roughly centered in the same place, the plot shows that, comparatively, the large MSAs have less variance than other location types in adoption of participation. In all, this figure provides a nuanced view of the marginal contribution of location. On the one hand, the figure supports global village because increases in local population size and density do not increase the average likelihood of participation. If anything, they lower it. On the other hand, it also shows that the worst locations all come from the lower tail of the distributions for rural areas and medium and small MSAs. In other words, not all locations outside of large MSAs had experiences consistent with global village.

[18] The results of the bivariate probit models and the robustness checks are not listed in any table. They are available from the authors upon request.

In Figure 2, the density estimate for large MSAs stochastically dominates those for small MSAs, medium MSAs, and rural areas. The center peak of the large MSAs' distribution is at a higher value than the others. The variance of enhancement adoption within large MSAs and rural areas also is less than that within small and medium MSAs. Once again, the worst locations all come from the lower tail of the distributions for rural areas and medium and small MSAs. This figure provides a visual depiction of the results in Table 5 that urban leadership better describes the geographic diffusion of enhancement than does global village.

In Table 6 we provide summary statistics on the marginal effects of the same regressions used for Figures 1 and 2. Again, the results show that establishments in larger MSAs are less likely to adopt participation and more likely to adopt enhancement.

We conducted a number of robustness checks. As noted, we were concerned that establishment location decisions might not be independent of Internet use. To control for this potential source of endogeneity, we re-estimated the model using only establishments that had been added to the Harte Hanks 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), qualitative results did not change.

We were also concerned about potential simultaneity bias at multi-establishment firms in the data. In Table 5, we included a control for multi-establishment firms to allow such firms to be more likely to adopt both participation and enhancement technologies; however, this variable is unable to control for the effects of unobserved differences in the behavior of other establishments within the same firm. For example, many firms will find it necessary to adopt enhancement technologies at a subset of locations, decreasing the likelihood of adoption as other establishments adopt. If adoption behavior of other establishments is systematically related in some way to location—if, for example, rural establishments tend to be in multi-establishment firms in which enhancement is adopted in other locations—then our coefficient estimates may be biased.

To control for this potential bias, we included variables capturing the behavior of other establishments within the same firm. In particular, we added variables measuring the percentage of establishments and total number of other establishments within the same firm adopting the dependent variable (i.e., participation or enhancement). Because this variable relies on the subset of establishments in our sample, it is imperfect. It will, however, enable us to say whether the inclusion of other establishment behavior influences our parameter estimates, and thus help us to gauge the potential extent of the bias. 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 (IV) techniques. IV regressions were calculated using Amemiya Generalized Least Squares estimators for probit regression with endogenous regressors. Our instruments for these variables are the average population and density of the locations of other establishments in the same firm. These are correlated with adoption decisions at the firm's other establishments, but not at the establishment of interest. These robustness checks make little difference to the estimated relationship between density and Internet adoption; the results contrasting global village and urban leadership hypotheses remain unchanged.

We tried other robustness checks. We experimented with different specifications, using different location variables (e.g., CMSA dummies), different firm controls (e.g., revenue, private/public), and alternative measures of population size and density. We also tried weighting the probit regressions by three-digit NAICS/states and two-digit NAICS/MSAs, as well as not weighting. In all cases the results remained similar.

5.2 WEI and CEI Investment

We divided both participation and enhancement into WEI and CEI and re-estimated the baseline MSA-size regressions on the decision to adopt WEI and CEI participation and enhancement. Because some of these narrowly defined margins of investment relied on information from the Harte Hanks long survey, our main results in Columns 1 and 4 are estimated on the sub-sample that received the long survey.

Parts A and B of Table 7 identify the geographic variation in adoption for WEI and CEI participation. Controlling for industry and establishment characteristics, Column 1 shows that location has little effect on the decision to adopt WEI participation technologies. For CEI technologies, the data in Column 4 show that increases in location size have a statistically significant, if economically small, negative impact on adoption. Large MSAs are 0.7% less likely than rural areas to have adopted participation by the end of 2000. The difference between the small MSA and large MSA dummies are statistically significant at the 5% level; however the effect is economically small when compared to CEI participation rates of 80.6%. We also examined statistical differences between technologies. We ran a bivariate probit model of the joint decision to adopt WEI and CEI participation and tested whether the MSAs dummies were significantly different from one another. The medium MSA estimate for CEI was lower than that for WEI at the 5 percent level. Because of the large standard errors for WEI relative to the point estimates, none of the other parameter estimates on the MSA dummies were significantly different.

Parts C and D of Table 7 show that the role of location varies across CEI and WEI enhancement technologies. In Column 1 we show that establishments located in large MSAs are 3.4% more likely to adopt WEI enhancement than those in rural areas (1 % significance) and 1.2% more likely to adopt than those located in small MSAs (10% significance). Both these differences are significant at the 1% level. In contrast, for CEI enhancement, establishments in large MSAs are only 1.1% more likely to adopt than rural establishments (1% significance) and no more likely to adopt than those in small MSAs. Again, to see whether these differences across technologies are significant, we estimated a bivariate probit model and compared parameter estimates for WEI and CEI. MSA dummies are significantly greater at the 1 percent level for WEI than for CEI: this is true whether we compare large MSA, medium MSAs, or the difference between large and small MSAs.

We ran several robustness checks. First, to ensure that our reduced sample was not influencing our results through a selection problem, we reran the regressions using the complete sample. The results, in Columns 2 and 5 of Table 7, are qualitatively the same for both participation and enhancement. Second, one potential concern with our baseline results is that the gross benefits of adopting some WEI technologies may be increasing in location size for establishments from multi-establishment firms. In other words, global village may apply to WEI technologies in multi-establishment firms. We examined whether our results were the same using only a sample of single-establishment firms. Again, the results, shown in Columns 3 and 6 of Table 7, are qualitatively similar.

In summary, this section examined two sets of hypotheses. First, we examined whether investment in WEI and CEI were consistent with global village or urban leadership. We showed that investment in WEI enhancement was consistent with urban leadership, while CEI participation was consistent with global village. Second, we examined whether WEI investment increases faster than CEI investment as location size increases. We found this to be true for enhancement. We offer two possible interpretations. First, these results could show that global village affects CEI enhancement. Second, they could mean that urban leadership is not driven by selection of IT-intensive firms into urban areas. In contrast, as location size increases, adoption of participation decreases for CEI but not WEI technologies. This pattern is consistent with the global village hypothesis.

6. INDUSTRY COMPOSITION

Industry composition matters. Table 3 shows that, on average, firms in large MSAs are 15% more likely to adopt participation than small MSAs. In contrast, the marginal effects in Table 5 show that being in a large MSA *reduces* the likelihood of adoption by over 3% relative to a small MSA. There are also differences between the average and marginal effects of location on enhancement. These contradicting results are explained by the different composition of industries in large and small MSAs. Large MSAs have relatively more establishments in leading industries. In this section, we explore the role of industry composition in detail.

6.1. What Does Industry Composition Explain?

We first show that industry composition explains a significant fraction of the variance in average adoption rates. In fact, Table 8 shows that industry composition explains much more of the variation in participation and enhancement rates than location does. Once industry is controlled for, the incremental contribution of location in the probit regressions is small. 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.

Next we show that the industries in large MSAs are more likely to adopt both participation and enhancement than industries in other areas. We use the marginal effects of each 3-digit NAICS that were estimated for (but not shown in) Table 5. For each MSA, we estimate the adoption propensity of its industries, weighted by their frequency in County Business Patterns. For example, suppose MSA *Q* has only two industries: 60% of large establishments are NAICS 511 (publishing) and 40% of large establishments are NAICS 234 (heavy construction). The marginal effects of NAICS 511 and 234 on participation adoption are 0.0455 and -0.1634 respectively. Therefore, the adoption propensity of the industries in MSA *Q* is -0.0381 ($0.0455\times0.6-0.1634\times0.4$)). Note that this adoption propensity is based on regressions that control for city size.

For both participation and enhancement, we calculate these propensities for each MSA and non-MSA state in the data. For participation, large MSAs have an average industry effect of -0.169 or -16.9%. Small MSAs have an average effect of -20.2% and rural areas have an average effect of -18.7%. For enhancement, large MSAs have an average effect of -7.4%, small MSAs have an average effect of -7.8% and rural areas have an average industry effect of -8.0%. Large MSAs tend to have more lead-user industries for both participation and enhancement.

Figures 3 and 4 display these differences in adoption propensity of industries across location types. Each figure displays the kernel density estimates of the marginal industry effect for each observation in the data. Figure 3 shows the results for participation and Figure 4 shows the results for enhancement. The data are divided into large MSAs, medium MSAs, small MSAs, and rural areas.

Both Figure 3 and Figure 4 show that the marginal effects on adoption of the industries in large MSAs are typically larger than those in other locations. Also, the marginal effects on adoption of the industries in rural areas are smaller than those in other locations. The figures provide further evidence that large MSAs have more lead-user industries and isolated areas have fewer lead-user industries.

Two broad conclusions emerge. First, this confirms the importance of controlling for industry composition when testing between global village and urban leadership hypotheses. Second, inferences about the role of location are fraught with omitted variable biases in the absence of such controls.

6.2. Are Industry and Location Complements or Substitutes?

We now explore how global village and urban leadership hypotheses interact with industry composition. In particular we explore whether industry and location effects are complements or substitutes. To identify between these alternatives, we reran 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 three-digit NAICS industries in our study or (2) the United States Department of Commerce's [30] top fifteen IT-using industries as reported by Daveri and Mascotto [9]. Both measures of IT intensity have strengths and weaknesses. The measure based on the top quartile selects on the basis of the dependent variable; the measure from Daveri and Mascotto's study 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.

Part A of Table 9 shows that there is little evidence of a complementary relationship between industry and location in participation; if anything, they are substitutes. We examine how differences in the marginal effect of our top quartile NAICS dummy vary across locations. An establishment in a top quartile NAICS and a large MSA is 2.6% more likely (1% significance) to adopt participation than an otherwise equivalent top quartile establishment in a rural area; however, establishments in top quartile NAICS and large MSAs are 2.8% less likely to adopt participation than are such establishments in small MSAs (1% significance).[19] The NAICS-level controls likely explain the lack of significance of the IT-intensive industry dummy (under both definitions). Perhaps because they are based on the Department of Commerce's [30] more general measure of IT use, the industry-location interactions in Part B of Table 9 are slightly less significant than in Part A. Still, they tell exactly the same story. An establishment in a lead-user industry (using the SIC for ranking) and large MSA is no more likely to adopt participation than an equivalent establishment in a small MSA.

In contrast to participation, the results for enhancement in Table 9 show a strong complementary relationship between industry and location. Part A shows that an establishment in a top quartile NAICS and a large MSA is 3.8% more likely (1% significance) to adopt enhancement than an otherwise equivalent top quartile establishment in a rural area. The difference between small MSAs and large MSAs is even larger and is significant at the 10% level. Large and medium MSA establishments are equally likely to adopt enhancement. The results based on the Department of Commerce's [30] more general measure of IT-intensity tell the same general story: An establishment in a lead-user industry and a large MSA is more likely to adopt enhancement than an otherwise equivalent establishment in a small MSA. In summary, industry and location appear to be complements for complex applications, i.e., -- urban leadership is especially important for leading industries in enhancement.

Co-invention theory suggests that adaptation of complex new technologies will be most sensitive to the presence of spillovers and complementary third-party services. Such complementarity may exacerbate agglomeration in use. The evidence is consistent with this theory, but is also not especially strong. Tables 3 and 4 show that use of frontier technologies remains widespread. Such an outcome cannot arise when strong complementarities (between location and industry) apply to a small set of locations and industries. Rather, the evidence is consistent with weak positive complementarities, as well as the existence of an abundance of industries near the frontier in many favorable locations.

7. CONCLUSIONS

Has use of the Internet been greater in urban areas, exacerbating local differences in the potential for economic growth? Or, as a communications technology, has the diffusion of the Internet been different from other IT and realized its promise of reducing the importance of location to economic activity? In this paper, we test competing views by examining hard data about the short-run decisions of firms to invest in the Internet. Summaries of our questions and findings are listed in Table 10.

For participation technologies, there is little evidence to support the urban leadership hypothesis. With controls for industry composition, we found that the global village hypothesis best explains the variation across locations. This was particularly so for technologies that lowered CEI coordination costs. In contrast, urban leadership best explains adoption behavior for complex enhancement technologies. We show that these overall results were driven by WEI enhancement technologies that played little role in reducing coordination costs with other establishments.

In both cases, large urban areas experienced less variation in adoption patterns than other areas. Outside of major urban centers, costs and benefits varied widely. Geographic variation in use was consistent with GPT theory: enhancement costs decrease more quickly as population density increases than do participation costs. Adopters of participation faced low technical hurdles to implementation, whereas adopters of enhancement faced high ones.

Industry composition played a major role in explaining the geographic variance in average rates of Internet adoption. This supported our focus on the marginal contribution of location, in contrast to prior studies. We found 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. Urban leadership appears especially strong in these cases. Nevertheless, our research shows that Internet participation did not exacerbate geographic inequalities by diffusing primarily to urban areas with complementary technical and knowledge resources. In terms of the basic technology, the Internet diffused at least as rapidly to isolated areas as to large cities.

The geographic pattern of adoption for enhancement may increase an urban/rural divide in productivity. Both the value of an application and its co-invention costs may vary with local conditions; in particular, urban areas may possess pooled resources that lower co-invention costs. In smaller MSAs and rural areas, thin technical labor markets alone could drive up costs of employing frontier Internet

[19] This figure is calculated by subtracting the marginal effect of the interaction term Small MSA*Top Quartile

technology. Such urban/rural divides may be exacerbated if technology-friendly establishments choose to locate in urban areas. Alternatively, such regional differences may be lessened if high participation rates in rural areas permit resource sharing across regions. With the right investments in CEI technologies, establishments in rural areas may be able to access services located in urban areas.

Our findings heighten several future research topics. First, research on the role of co-invention and the Internet 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 the impact of variation in labor market conditions, spillovers, and markets for technical support.

Second, variation between locations and industries in the benefits of Internet investment shaped regional productivity, and comparative advantage. Consequently, it may affect the long-run location decisions of firms and the agglomeration of economic activity. For example, inexpensive communications may mean that establishments relocate from high-cost–high-density areas to low-cost-low-density areas. These remain open questions. Further work should compare the location decisions in industries where CEI Internet technologies are prevalent with those in other industries.

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 diffusion model of adoption used in this study 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 will correlate positively with the rankings of location and industries uncovered in this study. This would imply that the investment dollars affiliated with the commercialization of the Internet were widely dispersed throughout locations and industries in the United States.

NAICS3 (5.39%) from the marginal effect of the interaction term Large MSA*Top Quartile NAICS3 (2.59%).

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Table 1
Open Questions

Open Question	Prediction	Testable Hypotheses
Global Village & Urban Leadership, Participation and Enhancement		
Is investment in participation and enhancement consistent with global village (urban leadership)?	$dNB/dx_i \leq 0$ $(dNB/dx_i > 0)$	Coefficient on rural areas $\geq$ small MSA $\geq$ medium MSA $\geq$ large MSA (Coefficient on rural areas< small MSA < medium MSA < large MSA)
As location size increases, does enhancement increase faster than participation -- consistent with GPT theory?	dNB/dx_i *for enhancement* > dNB/dx_i *for participation*	The difference between the coefficient for large and rural or small MSAs for enhancement is *greater* than the difference between the coefficient on large and rural or small MSA for participation?
Global Village & Urban Leadership, WEI and CEI Communication		
Is investment in **WEI** and **CEI** communications consistent with global village (urban leadership)?	$dNB/dx_i \leq 0$ $(dNB/dx_i > 0)$	Coefficient on rural $\geq$ small MSA $\geq$ medium MSA $\geq$ large MSA (Coefficient on rural < small MSA < medium MSA < large MSA)
Does **WEI** investment increase faster than **CEI** investment as location size increases-- consistent with global village?	dNB/dx_i *for* ***WEI*** > dNB/dx_i *for* ***CEI***	The difference between the coefficient on large and rural or small MSAs for **WEI** is *greater* than the difference between the coefficient on large and rural or small MSA for **CEI**?
Industry Composition		
Does industry composition explain geographic variance in adoption?	$dNB/dz_i > 0$; corr$(x_i, z_i) > 0$ and $\mathbf{dNB/dx > dNB/dx(.\vert z)}$	There is a positive correlation between IT-intensity and location size. Concentration of IT-intensive industries explains geographic variance in use.
Are industry and density complements (substitutes)?	$dNB/dz_i > 0$, $dNB/dx_i > 0$, and $d^2NB/dx_i dz_i > 0$ $(d^2NB/dx_i dz_i < 0)$	Industry composition and urban leadership both explain a part of adoption and the effect of IT-intensity is increasing (decreasing) as MSA size increases.

Notes :
$NB(x_i,z_i,) \equiv B(x_i,z_i) - C(x_i,z_i,)$
x_i describes geographic conditions such as population size and density.
z_i describes the IT-intensity of an industry.
Testable hypotheses describe the manifestation of each theory in probit models of decision to adopt participation and enhancement.

Table 2
National Internet Adoption Rates (in percentages)

	Weighted Average	**Unweighted Average**
Participation	88.6%	80.7%
Enhancement	12.6%	11.2%

Notes:
Source: Authors' calculations using the CI database and Census data.
Definitions for participation and enhancement are given in the text. See also Forman, Goldfarb, and Greenstein [13] for further documentation.
Unweighted average uses only CI database sample.
Weights are defined by Equation 3, as given in the text.

Table 3
Average Adoption by Size of Metropolitan Statistical Area (MSA)

Population	Average Participation	Standard Error	Average Enhancement	Standard Error	Number of Areas
Rural Area	85.1%	0.1%	10.6%	0.2%	49
Small MSA: < 250,000	75.5%	0.2%	9.9%	0.3%	143
Medium MSA: 250,000–1 million	84.9%	0.2%	11.2%	0.3%	116
Large MSA > 1 million	90.4%	0.1%	14.7%	0.2%	57

Notes:
Source: Authors’ calculations using CI database and census data.
Definitions for participation and enhancement are given in the text. See also Forman, Goldfarb, and Greenstein [13] for further documentation.
All calculations use weighted averages, where weights are defined by Equation 3, as given in the text. Standard errors are computed using the delta method.

Table 4: Metropolitan Statistical Areas with Over One Million People

CITY	Enhancement			Participation			Obs.	Population
	Rank	Rate	Std Err	Rank	Rate	Std Err		
Denver--Boulder--Greeley, CO	1	18.3%	1.3%	2	95.9%	0.7%	940	2,581,506
San Francisco--Oakland--San Jose, CA	2	17.0%	0.9%	1	96.4%	0.4%	2135	7,039,362
Salt Lake City--Ogden, UT	3	16.7%	1.7%	5	93.5%	0.8%	535	1,333,914
Minneapolis--St. Paul, MN--WI	4	15.9%	1.0%	9	92.7%	0.5%	1411	2,968,806
Houston--Galveston--Brazoria, TX	5	15.7%	1.0%	15	91.7%	0.6%	1413	4,669,571
Atlanta, GA	6	15.4%	1.0%	24	90.9%	0.6%	1426	4,112,198
Oklahoma City, OK	7	15.4%	2.0%	34	90.2%	1.1%	339	1,083,346
Dallas--Fort Worth, TX	8	15.3%	0.9%	13	92.1%	0.5%	1720	5,221,801
San Antonio, TX	9	15.3%	1.9%	6	93.3%	0.8%	395	1,592,383
Portland--Salem, OR--WA	10	15.1%	1.3%	14	92.1%	0.6%	776	2,265,223
Providence--Fall River--Warwick, RI--MA	11	14.9%	2.2%	7	93.0%	1.2%	290	1,188,613
Austin--San Marcos, TX	12	14.7%	1.9%	12	92.1%	0.7%	344	1,249,763
Cleveland--Akron, OH	13	14.7%	1.2%	3	94.8%	0.6%	1099	2,945,831
Tampa--St. Petersburg--Clearwater, FL	14	14.6%	1.3%	41	88.4%	0.9%	812	2,395,997
Memphis, TN--AR--MS	15	14.5%	1.8%	35	90.0%	1.0%	437	1,135,614
Seattle--Tacoma--Bremerton, WA	16	14.5%	1.2%	4	93.9%	0.5%	1012	3,554,760
Hartford, CT	17	14.4%	1.6%	33	90.2%	0.9%	500	1,183,110
San Diego, CA	18	14.3%	1.3%	20	91.5%	0.7%	738	2,813,833
Cincinnati--Hamilton, OH--KY—IN	19	14.2%	1.3%	37	89.7%	0.8%	772	1,979,202
Washington--Baltimore, DC--MD—VA--WV	20	14.2%	0.8%	30	90.4%	0.5%	2222	7,608,070
Chicago--Gary--Kenosha, IL--IN—WI	21	14.1%	0.7%	28	90.5%	0.4%	3431	9,157,540
Rochester, NY	22	14.1%	1.9%	32	90.3%	1.0%	373	1,098,201
Boston—Worcester--Lawrence, MA--NH--ME--CT	23	13.9%	0.8%	27	90.6%	0.5%	2231	5,819,100
Detroit—Ann Arbor--Flint, MI	24	13.8%	0.9%	21	91.4%	0.6%	1621	5,456,428
Kansas City, MO--KS	25	13.7%	1.3%	11	92.2%	0.6%	753	1,776,062
Raleigh--Durham--Chapel Hill, NC	26	13.7%	1.7%	17	91.6%	0.9%	398	1,187,941
Pittsburgh, PA	27	13.6%	1.3%	39	89.1%	0.8%	727	2,358,695
Indianapolis, IN	28	13.6%	1.4%	22	91.3%	0.8%	646	1,607,486
Charlotte--Gastonia--Rock Hill, NC—SC	29	13.6%	1.5%	26	90.7%	0.9%	618	1,499,293
West Palm Beach--Boca Raton, FL	30	13.6%	2.0%	47	85.9%	1.2%	299	1,131,184
Los Angeles--Riverside--Orange County, CA	31	13.5%	0.6%	10	92.5%	0.4%	4099	16,373,645
Miami--Fort Lauderdale, FL	32	13.5%	1.1%	25	90.9%	0.7%	1010	3,876,380
New York—Northern NJ--Long Island, NY--NJ--CT--PA	33	13.5%	0.6%	29	90.5%	0.4%	4775	21,199,865
Philadelphia-Wilm.-Atlantic City, PA—NJ--DE--MD	34	13.3%	0.9%	31	90.3%	0.5%	1745	6,188,463
St. Louis, MO--IL	35	13.2%	1.2%	38	89.7%	0.7%	936	2,603,607
Louisville, KY--IN	36	13.2%	1.6%	36	89.9%	1.0%	448	1,025,598
Columbus, OH	37	13.0%	1.5%	18	91.5%	0.9%	574	1,540,157
Buffalo--Niagara Falls, NY	38	12.9%	1.7%	40	88.5%	1.1%	393	1,170,111
Phoenix--Mesa, AZ	39	12.4%	1.1%	16	91.6%	0.7%	988	3,251,876
Greensboro--Winston-Salem--High Point, NC	40	12.2%	1.4%	23	91.1%	0.9%	570	1,251,509
Grand Rapids--Muskegon--Holland, MI	41	12.0%	1.5%	8	93.0%	0.7%	503	1,088,514
New Orleans, LA	42	11.9%	1.7%	46	86.0%	1.1%	386	1,337,726
Milwaukee--Racine, WI	43	11.7%	1.2%	19	91.5%	0.7%	855	1,689,572
Nashville, TN	44	11.7%	1.5%	49	84.6%	1.1%	466	1,231,311
Jacksonville, FL	45	11.3%	1.7%	42	87.6%	1.3%	373	1,100,491
Sacramento--Yolo, CA	46	11.8%	1.6%	44	87.0%	1.2%	427	1,796,857
Norfolk--Virginia Beach--Newport News, VA--NC	47	10.8%	1.7%	45	86.9%	1.2%	374	1,569,541
Orlando, FL	48	10.5%	1.3%	48	85.5%	1.0%	622	1,644,561
Las Vegas, NV--AZ	49	9.0%	1.4%	43	87.2%	1.2%	417	1,563,282
Standard Deviation		1.7%			2.5%			

Table 5
Effect of Population Size and Density on Adoption of Participation and Enhancement
(standard errors in parentheses)

		Participation			**Enhancement**		
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
A. Coefficients from (Weighted) Probit Regressions	Small MSA	0.0095			0.0198		
		(0.0249)			(0.0273)		
	Medium MSA	-0.0491			0.0449		
		(0.0186)**			(0.0179)*		
	Large MSA	-0.0262			0.0632		
		(0.0141)+			(0.0124)**		
	Ln(MSA Population)		-0.00288			0.00550	
			(0.00774)			(0.00713)	
	Medium-Low Density			-0.0170			0.0275
				(0.0190)			(0.0192)
	Medium-High Density			-0.0282			0.0860
				(0.0227)			(0.0198)**
	High Density			-0.0177			0.0577
				(0.0228)			(0.0195)**
	Log Likelihood	-33470.6	-33473.3	-33473.5	-28694.7	-28696.2	-28688.2
	Pseudo R^2	0.2252	0.2251	0.2251	0.0593	0.0592	0.0595

		Participation			**Enhancement**		
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
B. Marginal Effects from (Weighted) Probit Regressions	Small MSA	0.0021			0.00350		
		(0.0555)			(0.00487)		
	Medium MSA	-0.011			0.00800		
		(0.0043)**			(0.00328)*		
	Large MSA	-0.0058			0.0110		
		(0.0032)+			(0.00223)**		
	Ln(MSA Population)		-0.000648			0.000963	
			(0.00174)			(0.00125)	
	Medium-Low Density			-0.00385			0.00485
				(0.00432)			(0.00343)
	Medium-High Density			-0.00639			0.0154
				(0.00521)			(0.00367)**
	High Density			-0.00400			0.0103
				(0.00519)			(0.0035)**

Notes:
All regressions include dummy variables for three-digits NAICS, month that data was collected, survey type, and whether it was a multi-establishment firm. Employment and Employment squared were also included as controls. Population was measured at the MSA level. Robust standard errors, clustered by MSA, are in parentheses.
(1) & (4) Non-MSA is the base for these regressions.
(2) & (5) 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.
(3) & (6) 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	Standard Deviation Participation Marginal Effect	Median Enhancement Marginal Effect	Average Enhancement Marginal Effect	Standard Deviation Enhancement Marginal Effect
Rural	49	-0.0290	-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	-0.0460	-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

Notes:
Authors' calculation using estimates from probit models shown in Figures 1 and 2.
*N = 127 for enhancement because three small MSAs perfectly predicted non-adoption.

Table 7
Effect of Population Size and Density on Adoption of WEI Firm and CEI Adoption
(Standard errors in parentheses)

Participation

		WEI			*CEI*		
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
A. Coefficients from (Weighted) Probit Regressions	Small MSA	-0.000307	-0.00472	0.0318	0.019097	0.0209	0.0334
		(0.00222)	(0.0173)	(0.0294)	(0.0317)	(0.0200)	(0.0417)
	Medium MSA	0.0138	0.00497	0.0303	-0.0356	-0.0294	-0.0244
		(0.0160)	(0.0138)	(0.0215)	(0.0200)+	(0.0153)+	(0.0260)
	Large MSA	-0.00678	-0.00747	-0.0013	-0.0492	-0.0208	-0.0572
		(0.0127)	(0.0119)	(0.0151)	(0.0169)**	(0.0133)	(0.0238)*
	Log Likelihood	-30431.8	-52357.1	-17680.6	-15356.3	-34342.7	-8625.6
	Observations	53231	86879	30260	53231	86879	30119

		WEI			*CEI*		
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
B. Marginal Effects from (Weighted) Probit Regressions	Small MSA	-0.000102	-0.00181	0.0107	0.00280	0.00489	0.0048
		(0.00736)	(0.00661)	(0.00978)	(0.00459)	(0.00462)	(0.00587)
	Medium MSA	0.00457	0.00190	0.0102	-0.00536	-0.00700	-0.0036
		(0.00528)	(0.00527)	(0.00717)	(0.00308)+	(0.00369)+	(0.00393)
	Large MSA	-0.00225	-0.00285	-0.000431	-0.00727	-0.00490	-0.0084
		(0.00423)	(0.00457)	(0.00513)	(0.00256)**	(0.00316)	(0.00361)*

Enhancement

		WEI			*CEI*		
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
C. Coefficients from (Weighted) Probit Regressions	Small MSA	0.0801	0.0724	0.114	0.0330	0.0379	0.0183
		(0.0236)**	(0.0222)**	(0.0330)**	(0.0194)+	(0.0159)*	(0.0268)
	Medium MSA	0.0841	0.0931	0.0992	0.0462	0.0172	0.0370
		(0.0163)**	(0.0154)**	(0.0230)**	(0.0174)**	(0.0131)	(0.0192)+
	Large MSA	0.130	0.147	0.125	0.0334	0.00703	0.0013
		(0.0135)**	(0.0125)**	(0.0164)**	(0.0109)**	(0.00920)	(0.0138)
	Log Likelihood	-24608.8	-27269.8	-12499.4	-29910.4	-46272.2	-16510.5
	Observations	53227	86872	30260	53227	86872	30265

		WEI			*CEI*		
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
D. Marginal Effects from (Weighted) Probit Regressions	Small MSA	0.0217	0.0116	0.0274	0.0108	0.0117	0.00570
		(0.00662)**	(0.00372)**	(0.00841)**	(0.00642)+	(0.00498)*	(0.00848)
	Medium MSA	0.0226	0.0148	0.0235	0.0151	0.00530	0.0116
		(0.00456)**	(0.00261)**	(0.00570)**	(0.00577)**	(0.00404)	(.00611)+
	Large MSA	0.0340	0.0224	0.0285	0.0108	0.00215	0.0004
		(0.00367)**	(0.00208)**	(0.00393)**	(0.00356)**	(0.00282)	(0.00433)

Notes:

All regressions include dummy variables for three-digits NAICS, whether it was a multi-establishment firm, employment and employment squared as controls. Robust standard errors, clustered by MSA, are in parentheses. Non-MSA is the base for these regressions.

(1) & (4) include only establishments that received the supplementary Harte Hanks survey.

(2) & (5) include entire sample.

(3) & (6) include only establishments from single-establishment firms who received the supplementary Harte Hanks survey.

+ 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

Notes:
Source: Authors' calculation. Pseudo-R^2 from full model shown in Figures 1 and 2, and from subsets of coefficients controlling for industry and location effects.
Cities defined by CMSA.

Table 9
Interaction of Industry and Location Effects

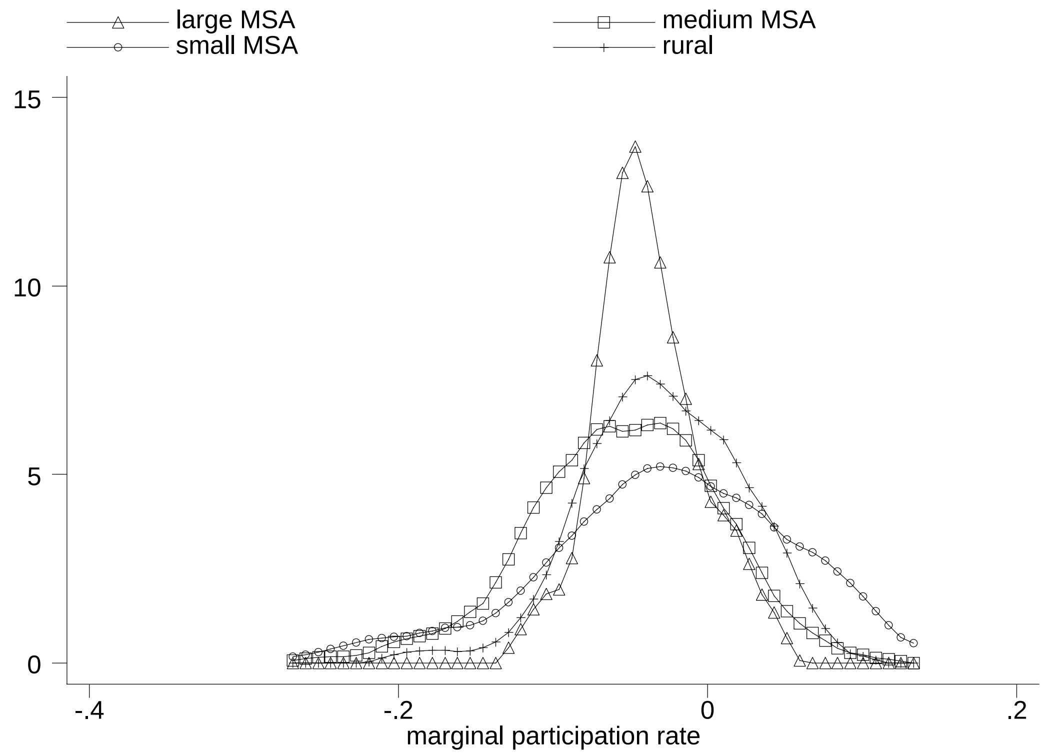
	A. Leading Internet Adopters (NAICS)				**B. Top IT-Using Industries (SIC)**			
	Participation		**Enhancement**		**Participation**		**Enhancement**	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Small MSA	-0.0127	-0.0029	0.0476	0.0085	-0.0217	-0.00492	0.0242	0.00428
	(0.0255)	(0.00580)	(0.0237)*	(0.0437)*	(0.0269)	(0.00617)	(0.0326)	(0.00586)
Medium MSA	-0.0640	-0.0147	0.00729	0.0013	-0.0710	-0.0163	0.0301	0.00533
	(0.0200)**	(0.00471)**	(0.00197)	(0.00346)	(0.0185)**	(0.00440)**	(0.0199)	(0.00358)
Large MSA	-0.0372	-0.0083	0.0243	0.0042	-0.0548	-0.0123	0.0301	0.00524
	(0.0148)*	(0.00337)*	(0.0116)*	(0.00204)*	(0.0152)**	(0.00346)**	(0.0130)*	(0.00230)*
Top quartile NAICS3	0.0460	0.0102	0.636	0.138				
	(0.505)	(0.110)	(0.454)	(0.118)				
Small MSA*	0.2791	**0.0539**	-0.0727	**-0.0121**				
Top quartile NAICS3	(0.0669)**	**(0.0108)****	(0.0871)	**(0.0139)**				
Medium MSA*	0.1618	**0.0335**	0.2020	**0.0397**				
Top quartile NAICS3	(0.0531)**	**(0.0101)****	(0.0450)**	**(0.00985)****				
Large MSA*	0.1205	**0.0259**	0.1998	**0.0382**				
Top quartile NAICS3	(8.0308)**	**(0.00629)****	(0.0291)**	**(0.00610)****				
IT intense SIC					0.0379	0.00844	0.0772	0.0138
					(0.0426)	(0.00943)	(0.0501)	(0.00912)
Small MSA*					0.2114	**0.0424**	0.0176	**0.00311**
IT intense SIC					(0.0689)**	**(0.0122)****	(0.0777)	**(0.00139)**
Medium MSA*					0.1583	**0.0329**	0.0838	**0.0153**
IT intense SIC					(0.0372)**	**(0.00712)****	(0.0391)*	**(0.00750)***
Large MSA*					0.1914	**0.0404**	0.1358	**0.0250**
IT intense SIC					(0.0227)**	**(0.00438)****	(0.0235)**	**(0.00459)****
Log Likelihood	-33464.7	-33464.7	-28674.1	-28674.1	-33436.5	-33436.5	-28668.1	-28669.1
Pseudo R^2	0.2253	0.2253	0.0600	0.0600	0.2260	0.2260	0.0602	0.0602

Notes:
All regressions include dummy variables for three-digits NAICS, month that data was collected, and whether it was a multi-establishment firm. Employment and Employment squared were also included as controls. Robust standard errors, clustered by MSA, 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

Table 10
Main Findings

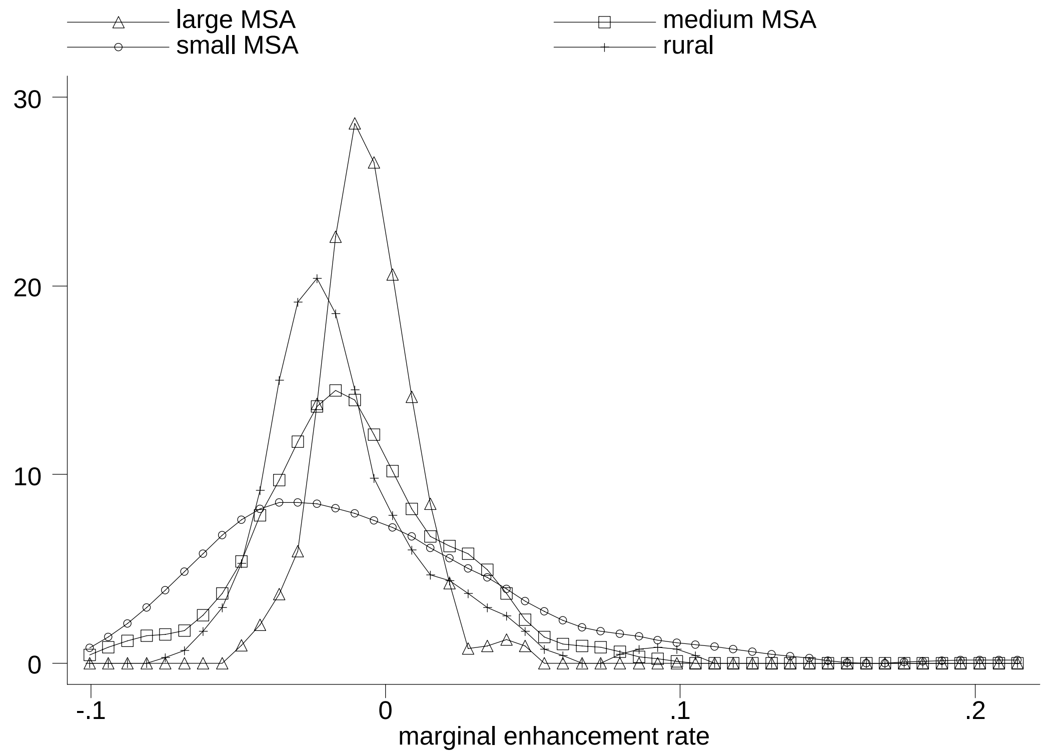
Open Question	Summary of findings	Source
Global Village & Urban Leadership, Participation and Enhancement		
Is investment in participation and enhancement consistent with global village (urban leadership)?	Overall, participation is consistent with predictions of global village. Overall, enhancement is consistent with predictions of urban leadership.	Section 5.1 Tables 5, 6 Figures 1, 2
Does enhancement increase faster than participation as location size increases?	Yes, and this is consistent with GPT theory.	
Global Village & Urban Leadership, WEI and CEI Communication		
Is investment in **WEI** and **CEI** communications consistent with global village (urban leadership)?	Only **WEI** enhancement is consistent with predictions of urban leadership. Only CEI participation is consistent with predictions of global village.	Section 5.2 Table 7
Does **WEI** investment increase faster than **CEI** investment as location size increases-- consistent with global village?	**CEI** investment is more sensitive **than WEI** investment to increases in location size, which is consistent with the predictions of global village.	
Industry Composition		
Does industry composition explain geographic variance in adoption?	IT-intensive industries tend to be in urban areas. Industry composition explains a high fraction of the variance in participation and enhancement, but not all of it.	Section 6.1 Tables 8, 9 Figures 3,4
Are industry and density complements (substitutes)?	Overall, findings are consistent with industry and density being complements for investments in enhancement in urban areas.	Section 6.2 Tables 8, 9

Figure 1
Comparison by City Size of Location Marginal Effects for Participation



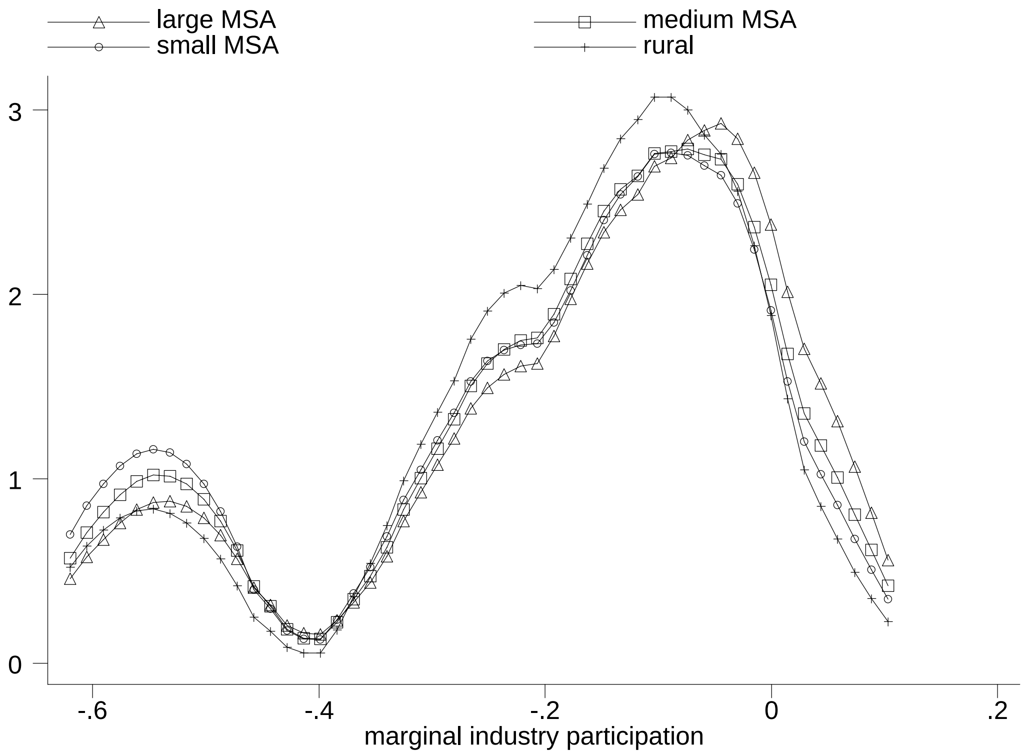
Notes:
Source: Authors' calculation.
Figure shows Epanachnikov kernel density estimates of the marginal effect of location on participation, by city size. Uses baseline probit in the model in Equation 2.

Figure 2
Comparison by City Size of Location Marginal Effects for Enhancement



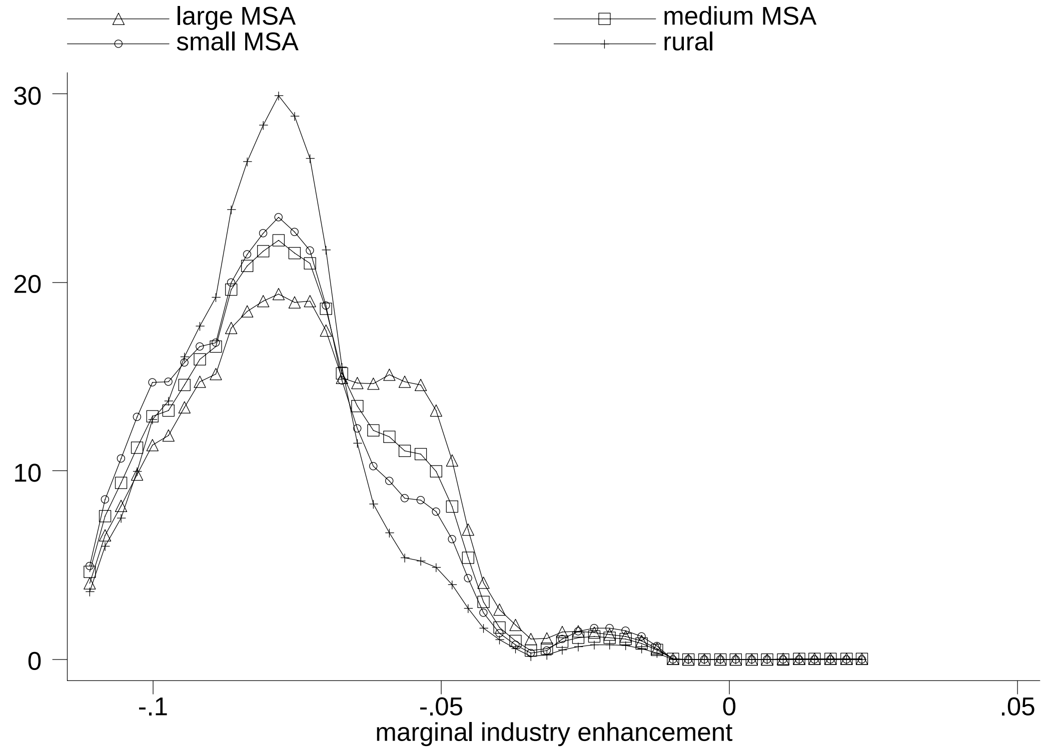
Notes:
Source: Authors' calculation.
Figure shows Epanachnikov kernel density estimates of the marginal effect of location on enhancement, by city size.
Uses baseline probit the model in Equation 2.

Figure 3
Industry Marginal Effects for Participation by City Size



Notes:
Source: Authors' calculation.
Figure shows Epanachnikov kernel density estimates of the marginal effect of industry on participation, by city size.
Uses baseline probit in the model in Equation 2.

Figure 4
Industry Marginal Effects for Enhancement by City Size



Notes:
Source: Authors' calculation.
Figure shows Epanachnikov kernel density estimates of the marginal effect of industry on enhancement, by city size.
Uses baseline probit in the model in Equation 2.