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EVIDENCE ON LEARNING AND NETWORK EXTERNALITIES IN THE DIFFUSION OF HOME COMPUTERS

Austan Goolsbee
Peter J. Klenow

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ABSTRACT

In this paper we examine the importance of local spillovers such as network externalities and learning from others in the diffusion of home computers using data on 110,000 U.S. households in 1997. Controlling for many individual characteristics, we find that people are more likely to buy their first home computer in areas where a high fraction of households already own computers or when a large share of their friends and family own computers. Further results suggest that these patterns are unlikely to be explained by city-specific unobserved traits. Looked at in more detail, the spillovers appear to come from experienced and intensive computer users. They are not associated with the use of any particular type of software but do seem to be highly tied to the use of e-mail and the Internet, consistent with computers being part of a local information and communications network.

Austan Goolsbee
Graduate School of Business
University of Chicago
1101 E. 58th Street
Chicago, IL 60637
and NBER
goolsbee@gsb.uchicago.edu

Peter J. Klenow
Graduate School of Business
University of Chicago
1101 E. 58th Street
Chicago, IL 60637
and NBER
pete.klenow@gsb.uchicago.edu

I. Introduction

In this paper we empirically examine the importance of local spillovers – such as network externalities and learning from others – in the diffusion of home computers. Technology diffusion plays a central role in many theories of development and economic growth.[1] Some recent studies have singled out the diffusion of computers as an engine of growth and as a potential source of fundamental labor market changes.[2] And network externalities are of recurring interest in industrial organization and public economics.[3]

We employ a database on the computer ownership and purchase decisions of more than 110,000 U.S. households.[4] Our notion is that people without computers may learn about the technology from their computer-owning friends and neighbors, or benefit from the size of the local computer "network", say because they can share software or communicate with one another. If so, there may be positive spillovers of existing computer owners on people considering adoption.

Because of the possibility of unobserved common traits across households, establishing the existence of local spillovers is difficult. People who live in places where a high share of people already own computers may have a greater affinity for technology, even if they do not already own a computer, and therefore may be more likely to adopt. This problem of common traits pervades empirical work on local effects. Thus, we will employ several strategies to test whether unobserved common traits, or still other alternatives to network or learning benefits, can explain our findings.

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[1] Examples are Grossman and Helpman (1991), Parente and Prescott (1994), and Barro and Sala-i-Martin (1997).

[2] Discussions of computers as engines of growth or General Purpose Technologies can be found in Bresnahan and Trajtenberg (1995), Greenwood and Yorukoglu (1997), Helpman and Trajtenberg (1998), and Andolfatto and MacDonald (1998). The debate over the role of computers in the transformation of the labor market includes Krueger (1993), DiNardo and Pischke (1997), and Autor, Katz, and Krueger (1997). Friedberg (1997) examines the impact of computers on the retirement decisions of elderly workers.

[3] Farrell and Saloner (1985) and Katz and Shapiro (1986) provide early analyses of network externalities. Economides (1996) surveys the more recent literature. Dybvig and Spatt (1983) give an overview of the implications for public economics.

[4] For investigation into the adoption of computers by firms, see Bresnahan and Greenstein (1996) and Bresnahan, Stern, and Trajtenberg (1997).

The existence of learning or network externalities in computer adoption could have important policy implications. Learning externalities could mean that the rate of adoption is too slow and possibly justify subsidies to computer and Internet adoption.[5] An important caveat, however, is that evidence of learning and network *spillovers* is not the same as evidence of learning and network *externalities*. The recipients of spillover benefits may compensate the providers (e.g., "I'll take you to lunch if you will show me how to use this computer"). In keeping with the existing literature, we will refer to learning and network externalities, but the distinction between externalities and spillovers matters for any policy discussion.

In the empirical results that follow, we find evidence consistent with local spillovers in home computer adoption. Using instruments, additional control variables, and a variety of tests and sample periods we find little evidence that the effects are the result of unobserved common traits within cities, local industry composition, availability of computer retailers, or peer pressure ("keeping up with the Joneses").

The data do suggest that the spillovers are concentrated in local areas and among family and friends. The spillovers appear to be greatest from experienced and intensive computer users. The spillovers do not appear to be tied to the use of any particular type of software (spreadsheets, word processors, graphics, games, family budgeting) but are highly tied to the use of e-mail and the Internet. This is consistent with the idea that the computer serves as a part of a local information or communication network.

The rest of the paper proceeds as follows. In section II we describe previous work in related areas. In section III we describe the dataset. In section IV we outline our empirical specification and present basic results on local spillovers. In section V we consider the

[5] See Hausman (1998) for a description and evaluation of the existing $2.25 billion annual U.S. federal subsidy for public school and library Internet access financed by a special tax on phone service. There have been more ambitious (albeit geographically concentrated) subsidies as well, including the Blackburg Electronic Village program in Virginia and the Information Age Town program in Ennis, Ireland. In these cities attempts were made to put a computer in every household and school and to connect everyone to the Internet (for descriptions of these programs see Yaukey, 1997 and MacCarthaigh, 1997).

evidence about unobserved common traits. In section VI we investigate the nature of the spillovers try to identify the source of the network benefits. In section VII we conclude.

II. Related Literature

A. Learning and Network Externalities

The issues raised in this paper about learning from others and about network externalities are certainly not new. Network externalities can affect the diffusion of technology. The literature in this area is voluminous (see the survey by Economides, 1996). As shown in early work by Farrell and Saloner (1985) and Katz and Shapiro (1986), network externalities can lead to suboptimally slow adoption, suboptimally fast adoption, or even adoption of an inferior technology.[6] Examples of empirical work examining such issues includes Gandal (1994), Saloner and Shepard (1995), Berndt and Pindyck (1998), and Gowrisankaran and Stavins (1999).

Similar to network benefits, learning from others can also influence the spread of technology as argued in Young (1991), Chari and Hopenhayn (1991), Lucas (1993), Jovanovic and MacDonald (1994), and Andolfatto and MacDonald (1998). In his classic study of the diffusion of hybrid corn in the U.S., Griliches (1957) found evidence consistent with late-adopters learning from early-adopters. More recent micro-level empirical studies of learning from others include Jaffe, Trajtenberg, and Henderson (1991), Irwin and Klenow (1994), Foster and Rosenzweig (1995), and Besley and Case (1997).

B. Local Conditions and Peer Groups

In the empirical work we will examine how local conditions affect the rate of computer adoption to test learning and network hypotheses. This is similar to the literature examining peer group effects on social outcomes such as crime and teen pregnancy. The presence of local

[6] The literature on herding and learning from the behavior of others, recently surveyed by Bikhchandani et al. (1998), contains similarities to both the learning and network literatures discussed here.

spillovers has been investigated in various settings and using various methods by Case and Katz (1991), Evans, Oates and Schwab (1992), Case, Hines, and Rosen (1993), Borjas (1995), Glaeser, Sacerdote and Scheinkman (1996), and O'Regan and Quigley (1996).

This literature has generally found that local effects are important but has also stressed that unobserved heterogeneity may bias empirical work toward finding local effects. Individuals may be more likely to do something when those around them are doing it because they share unobserved common traits. Evans et al. (1992), for example, show that instrumenting for selection into schools removes the entire estimated impact of peer groups for teen pregnancy. The problem of unobserved common traits and sorting is also known as Tiebout bias in the spirit of Tiebout (1956). We will deploy instruments and controls to address the potential bias from unobserved common traits problem.

III. Data

The data we use come from a proprietary December 1997 mail survey of Forrester research called *Technographics 98*. Forrester is a marketing research company specializing in the information economy. The fieldwork for the survey was conducted by the NPD Group. In it, they interviewed more than 110,000 American households to determine their ownership patterns for computers and other electronic goods. The detail in the survey exceeds that in government surveys that include computer information, such as the CPS or the Consumer Expenditure Survey. The sampling methodology is proprietary but is meant to ensure a nationally representative sample. More details on the *Technographics* program can be found in Bernhoff, et al. (1998). Its purpose is to provide technology, communications, and consumer marketing companies with information for evaluating the consumer segments for their products. The Forrester data is widely respected in the industry and private sector companies pay significant amounts of money to get access to it.

For each respondent the dataset contains demographic information, including gender, race, income, education, age, marital status, whether they have children under 18, whether they use a computer at work, whether they run a business from home, and their state and broadly defined metropolitan area of residence.[7] The dataset also contains information on how much they watch television, their ownership of various electronic goods, and even some attitude variables such as ratings from one to ten of how much they "like technology". All of this information is gathered in December of 1997.

For anyone with a computer in 1997, the survey also contains information on how many computers they have, how many they have ever had, when they bought their first computer, when they bought their (up to) three most recent computers, how often they use their computer and whether they have Internet access. For those without computers, the survey includes (self-reported) information on how likely they are to buy a computer in the next year and what share of their friends and family use computers.

Using this information we are able to calculate what fraction of people in a city had a computer last year (assuming no one moved) and what share of 1996 non-owners bought their first computer in 1997. We can also keep aging the data backward. We cannot get a true panel, however, because household information such as family composition is given only at the time of the survey.[8]

Table 1 provides summary statistics for computer ownership. The data show that ownership varies within the population in predictable ways. Owners are better educated, richer, and so on. The computer ownership rate in the Forrester data matches well to rates independently published by the Consumer Electronics Manufacturing Association. We also found only modest differences when we cross-checked median income, age, and marital status for several states against data reported by the U.S. Bureau of the Census (1998). Although our analysis will focus on spillover effects within metropolitan areas, we present a map of the 1997

[7] The respondents are divided into 207 metropolitan areas that are defined by the television market they reside in. These areas are generally larger than comparable SMSAs. The San Francisco area, for example, includes all of the Bay Area.

[8] For a discussion of the potential problems with such retrospective data see Besley and Case (1993) or Hamermesh (1998).

computer ownership rates by state in Figure 1. Figure 2 is a histogram of ownership rates by metropolitan area.

IV. Empirical Specification and Basic Results

A. Empirical Specification

We concentrate on the dichotomous choice facing people who do not yet have a home computer at the start of the year of whether to buy a computer. For household i in year t, call this decision y_{it}, where $y_{it} \in \{0,1\}$. If p^*_{it} is household i's reservation price in year t and p_{it} is the market price facing household i in year t, then

$$y_{it} = 1 \text{ if } p^*_{it} \geq p_{it}$$
$$y_{it} = 0 \text{ if } p^*_{it} < p_{it} \ .$$

Consider a household that buys in year t. Since this is the first purchase, this is the first year in which the market price of a computer has been below the household's reservation price. This may have come about because the market price fell, the household's reservation price rose, or some combination. We specify that

$$\text{(1)} \qquad \text{Probability}(y_{it} = 1) = \lambda \, \text{CITY\%}_{t-1} + \beta \, x^o_i + x^u_{it} + c^u_t + u_{it} \,.$$[9]

$\text{CITY\%}_{t-1}$ is the variable of interest. It is the fraction of households in the city having a computer in the previous year. If there are local learning and network externalities, then people who do not own computers who are living in areas where owners are prevalent will be more likely to buy one. This should appear as a positive coefficient on CITY% in (1).[10]

[9] We use a linear probability model for simplicity, particularly in the IV context. Our basic results were the same using a probit model.

[10] This model is analagous to epidemiology models in which an infectious disease spreads more quickly the larger the fraction of the population infected. In the marketing literature, this is known as the Bass (1969) model, and many examples of its use can be found in the survey by Mahajan, Muller and Bass (1993). The

The x_i^o are household observables. In the basic specification these are age, education, income, gender, race, marital status, the presence of children, whether the respondent uses a computer at work, and whether the respondent runs a business from home. There is no time subscript since we have this data for 1997 only.

The x_{it}^u are household unobservables correlated with $CITY\%_{t-1}$ but uncorrelated with x_i^o. Although families may not sort into cities based on their propensity to own computers, they may sort on characteristics that are correlated with that propensity. To generate x_{it}^u, however, the sorting must be over and above sorting on observables like income, age, education, or use of a computer at work, because these are controlled for in (1). We have in mind something like technological sophistication that is correlated across households within cities but is not captured by the observables. Measurement error in x_i^o (e.g., errors in reported income) could also contribute to x_{it}^u.

The c_t^u are city-level unobservables such as the quality and price of Internet access, the price of computers, and the density of computer stores. It is important to note, though, that these differences may arise in response to city differences in computer ownership rates, and thus themselves may represent network externalities. Finally, the u_{it} are idiosyncratic household unobservables.

The unobservable terms clarify the potential sources of bias in a regression such as (1). In the spirit of the peer group literature, if the CITY% is positively correlated with the x_i^u, then the estimated local effect $(\widehat{\lambda})$ will be biased upward. If people in Silicon Valley love technology, they may be more likely to own computers and to buy them even if they do not yet own them. This will spuriously make the spillover seem large. Similar biases arise when differences in city specific unobservables, c_t^u, are large. On the other hand, the estimates may have a downward bias because of survivor bias (see Heckman and Singer, 1985). If the only people living in Silicon Valley who do not own computers in 1997 actually hate technology and

model is also very similar to the work of Glaeser (1997) on learning within cities and resembles work on local interactions such as Durlauf (1993) and Brock and Durlauf (1995).

will *never* buy a computer, this will create a downward bias in our estimated $\widehat{\lambda}$. In either case, instrumenting is necessary.

B. Basic Results

We start, in column 1, by presenting the traditional ownership regression that suffers from potentially large biases. The dependent variable is a {0,1} for whether the individual owns a computer and the independent variable of interest is the mean ownership rates of other people in the metropolitan area. Not surprisingly, a household is more likely to own if other households in the same metro area own (coefficient .369, standard error .028), even controlling for household characteristics such as education, income, age, and whether a computer is used at work. This coefficient is bound to be biased upward because of unobservable city features and correlated household observables. In contrast to this regression of ownership on ownership of others in the city, we now turn to regressions of *first-time adoption* on *lagged* ownership of others in the city.

We are more interested in the impact of lagged ownership on the probability of first-time adoption for two reasons. First, it may mitigate the bias from correlated household unobservables. By looking only at non-owners and asking if they are more likely to adopt if surrounded by more owners, we are isolating people who are demonstrably different from computer owners. Second and more important, the economic logic of learning and network externalities suggests that the stock should affect the flow. In the case of learning, a bigger stock means more owners from which to learn how to use and buy a computer, promoting adoption. In the case of network externalities, a bigger stock means a bigger network in which to participate.[11]

[11] In fact, theory suggests that what should matter is the expected size of the network over the entire lifetime of the computer. This could also hold true for learning if adopters expect to be learning from other owners even after they have adopted. This is quite difficult to deal with appropriately, however, since the path of computer ownership will be strongly affected by the hard-to-predict future rate of decline of computer prices.

In column 2 of Table 2 we look at individuals who do not own computers at the end of 1996 and ask whether they are more likely to buy one in 1997 if there were many owners in their city in 1996. The estimated coefficient on local ownership rates, λ, is listed in the first row. The estimate of λ is positive and highly significant, suggesting that local spillovers may be important. The t-statistic is over 6.[12] It is also economically important. The point estimate of .10 implies that, controlling for household-specific observables, a non-owner in a city with 10 percentage points higher computer ownership in 1996 has a 1 percentage point higher probability of making a purchase in 1997.[13] This is substantial relative to the 1997 mean adoption rate for non-owners of 7.8%. The levels coefficient in column x is likely to be higher than the adoption coefficient both because of the cumulative nature of the levels regression and because it is more susceptible to the bias from common unobservables across people.

The other coefficients listed in column 2 have predictable signs. Households with more income and education are more likely to buy their first computer. Using a computer at work, running a business from home, and having children in the household are also associated with a higher probability of first purchase. Since this is a linear regression, the coefficients are marginal probabilities. For example, having a child between 6 and 17 in the household means a 4.2 percentage point higher probability of buying. The largest marginal effect (as well as the largest t-statistic) is on using a computer at work. This raises the probability of purchase by 7 percentage points, almost doubling it at the mean of the covariates.

Columns 3 through 5 estimate the same specification but for different years. Column 3 looks at the purchase decisions of non-owners in 1996 as a function of city ownership in 1995.[14] Column 4 examines the decision in 1995 as a function of ownership in 1994. In both cases, the estimated coefficients remain large, positive and highly significant. The ceofficient in 1996 is .142. The coefficient in 1995 is .135. In column 5 we examine the responses of 1997

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[12] All of the standard errors in the paper are corrected for the fact that the CITY% does not vary by household.
[13] We obtained very similar results using the share of people in a city who either own a computer at home or use a computer at work for CITY% (rather than just the share who own a computer at home).
[14] The observables of the individual are given only in 1997 so we use the same values for earlier years.

non-owners to the question "How likely are you to purchase a computer in the next year?" (rated from 1 to 10) as a function of city ownership in 1997. Here we construct a pseudo-probability of buying by subtracting 1 and then dividing by 10. This gives a scale from 0 to .9. In this prospective purchase regression, increased ownership rates in a city are again associated with significantly higher probabilities of buying. The coefficient of .106 for prospective purchases is close to our baseline estimate of .102 for actual purchases.

The results in Table 2 show a robust coefficient on CITY%, consistent with local learning and network benefits. But this is also consistent with unobserved common traits between the new adopters and existing owners, so in the next section we test whether the coefficient can be attributed to this alternative hypothesis. Before doing so, however, we illustrate the quantitative importance of the spillover implied by the point estimate for 1997.

Summing equation (1) across households within a city yields

$$\text{(2)} \qquad \frac{f_{ct}}{1-F_{c,t-1}} \;=\; \lambda\, F_{c,t-1} \;+\; \beta\, x^{o}_{c} \;+\; c^{u}_{t} \;+\; x^{u}_{ct}\,,$$

where f_{ct} is the fraction of city c households who buy their first computer in year t and $F_{c,t-1}$ (= CITY%$_{t-1}$) is the fraction of households in city c who own a computer in year $t - 1$. i.e., f and F are the density and cumulative density, respectively, of computer adoption (first-time computer purchase). We then have

$$\text{(3)} \qquad F_{ct} \;=\; F_{c,t-1} \;+\; f_{ct} \qquad F_{c,t-1} \;+\; [1 - F_{c,t-1}]\,[\,\lambda\, F_{c,t-1} \;+\; \beta\, x^{o}_{c} \;+\; c^{u}_{t} \;+\; x^{u}_{ct}\,]\,,$$

which is precisely the Bass (1969) diffusion model. Analogous to models of a contagious disease, the fraction of the city with a computer this year (F_{ct}) is equal to the fraction last year ($F_{c,t-1}$) plus the hazard rate for buying a computer ($f_{ct}/(1 - F_{c,t-1})$) times the fraction of the population which is at risk $(1 - F_{c,t-1})$. When λ 0, the hazard is rising in the fraction of the population who own in the previous period.[15]

For non-owners, the 1997 hazard rate in our sample was approximately 8%. Given our baseline estimate of $\lambda = .10$ and an average $F_{c,t-1}$ across cities of 40% in 1996, $\lambda^* F_{c,t-1}$ contributed 4 percentage points to the 8% hazard rate. The remaining terms $(\beta\, x_c^o + c_t^u + x_{ct}^u)$ contributed the other 4 percentage points. Thus in 1997 one half of the adoption rate may have come from local spillovers. In short, if our coefficient reflects spillovers, then spillovers substantially affect the speed of diffusion.

V. Unobserved Common Traits

The most obvious alternative explanation for the positive coefficient on local ownership is that it represents nothing more than the existence of unobserved common traits across people in a city. In technologically sophisticated places where a large fraction of the population already owns computers, non-owners may also be more sophisticated and thus likely to buy computers, even controlling for observables like education and income. We take three approaches to get around the problem of unobserved common traits.

A. Controls for Unobservable Sophistication

If the local spillover is coming from unobservable technological sophistication, then adding some measures of an individual's sophistication ought to reduce the coefficient on CITY %. In column 2 of Table 3 we attempt to do this by including a variety of proxies for sophistication. (For comparison, column 1 repeats the baseline regression results from column 2 of Table 2). These additional variables include ownership of several types of consumer electronics (satellite dish, big-screen TV, cordless phone, CD player, component stereo system, VCR, and answering machine), dummies for the amount of television the respondent watches

[15] Notice that in this model computers can spread even if there are no spillovers, say because of falling prices interacting with the determinants of household reservation prices $(\beta\, x_c^o + c_t^u + x_{ct}^u)$.

per month, and subjective answers (from one to ten) to questions of how well the statements "I like technology," "technology is important to me," and "I like to spend time learning about new technology products" describe their personality. The coefficients on these extra variables are not listed to economize on space (they are all significant with predictable signs).[16] Column 2 makes clear that, despite their significance, these additional variables do not change the estimated local effect. The coefficient is still positive and significant, with an almost identical point estimate (.101 vs. .102).[17]

The next regression is motivated by the debate over the impact of computers on wages. DiNardo and Pischke (1997) show that, while using a computer seems to raise wages substantially (Krueger, 1993), so does using a pencil and sitting down while working. Further, controlling for pencil use and working while sitting often lowers the estimated wage effect of computers substantially. They argue that this casts doubt on a causal interpretation of the computer coefficient.

To apply this to our context, column 3 of Table 3 adds to the regression of column 2 the fraction of households in the city who own each of the seven consumer electronic goods. We do not think there are plausible learning or network benefits for computer adoption arising from widespread use of stereos, VCRs, and so on. Thus if these variables matter and lower the coefficient on the fraction of people owning computers, it would cast doubt on a spillover interpretation. We find in column 3, however, that the results change little. The local effect of computer ownership is still positive and significant (t-statistic of 3) and has an almost identical magnitude (.104 vs. .102). Although we do not list the other coefficients for space reasons, none of the seven spurious ownership fractions is positive and significant.

Adding variables correlated with unobservable sophistication does not seem to change the estimated importance of spillovers.

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[16] Ownership of other electronics could also be proxying for lifetime income, which the current income variable measures with error.

[17] Because many people have missing values for at least one of the additional variables, the sample size is smaller in column 2 and the two regressions are not directly comparable. Without the additional variables but with the smaller sample, however, the coefficient is almost identical to our baseline coefficient in column 1.

B. Instrumental Variables

Our second strategy for dealing with household unobservables is instrumenting. Instruments must be relevant (correlated with the fraction of the city that owns computers) and valid (uncorrelated with the household's unobservables).

In column 4 of Table 3 we use the city means of the 10 household variables (education, income, age, and so on) that appear in the baseline regression in column 1. Positive local externalities mean that, conditional on its characteristics, a household should be more likely to buy its first computer if it is surrounded by households with observables favorable to computer ownership. For example, a childless household surrounded by households with kids should be more likely to adopt than a childless household surrounded by childless households. Thus city means should be relevant instruments, and they are (the 1st-stage R^2 is 0.88).[18] Are city mean observables (call them x^o) valid instruments, i.e., uncorrelated with household observables (x_i^u)? One might worry that they are positively correlated because, say, cities with lots of households with children are filled with the more technologically savvy. But note that x_i^u is orthogonal to x_i^o by construction because a household's observables are included in the regression. For example, the coefficient on kids in the household should incorporate any correlation between the household's sophistication and the presence of kids. For this reason, city mean observables would not be correlated with household unobservables simply because cities with kids tend to be filled with technological sophisticates. It would have to be that, controlling for whether a household includes kids, it is more savvy the higher the fraction of households in the city with kids.

As column 4 of Table 3 shows, using these city means as instruments gives an almost identical answer to OLS (.104 vs. .102), with the CITY% coefficient estimated quite precisely (t-statistic of 6.1). And we cannot reject the overidentifying restrictions at the five percent

[18] Case and Katz (1991) develop this insight and propose a likelihood ratio test of, in our example, whether the city means for the observables matter for individual decisions. When we did this test using our data, we easily rejected the hypothesis that there are no local effects.

level (p-value of .16).[19] We obtained similar results (and also could not reject overidentifying restrictions) when we excluded various subsets of the instruments such as, respectively, the two work variable city means, the income and education city means, and the race city means. Thus, for example, adoption is more likely if a household is surrounded by households with kids, controlling for whether the household has kids or not.

Next we consider the weather in the city as an instrument because of its exogeneity. It would be a relevant instrument if a good climate, as an amenity, tends to attract high income people who will buy more computers (but not valid if people sort into cities with good climates based on their technological sophistication). We use the overall climate score for an area given by the *Places Rated Almanac* (for those areas not included in the *Almanac*, we use the closest alternative location). The data show that places with higher climate scores do have significantly higher incomes and the first-stage R^2 was .19. With climate as the only instrument (column 5), the coefficient on city ownership is .163 (standard error of .046).

Our instrumental variables results also suggests that unobserved common traits are not the source of the city spillovers.

C. Spillovers by Type of Owner

Our third check for whether the estimated spillover is the result of unobserved common traits within a city uses information on who the existing owners are. Our results show that having a high ownership of computers makes non-owners more likely to adopt in the coming year. If this comes from common traits across owners and non-owners (such as technical sophistication), this predicts that the estimated spillovers should be largest from owners who are most like the non-owners. They are most likely to share unobserved common traits. The network and learning spillover story, however, predicts something quite different. It predicts

[19] In testing the over-identifying restrictions, we take account of the fact that the data are grouped by city using the technique of Hoxby and Paserman (1998).

that experienced, heavy users should be the most important influence on potential adopters because they have the most information and are the most valuable members of a local network.

Using the information in the survey on how many computers a household has ever owned, we divide city ownership into two groups: people who have owned two or more computers in their lifetime (19% of all households) and people who have owned only one in their lifetime (also 19% of all households). We would expect non-owners to have more traits in common with people owning their first computers than with experienced owners, so if the unobservables bias explanation is correct there should be particularly high rates of adoption in places where there are many first time owners. On the other hand, if the spillover explanation is correct, since multiple-computer owners are likely to be better informed, have more software to share, and so on, the coefficient on experienced users should be larger. The results, presented in column 6 of Table 3, show that, in fact, multiple-lifetime-purchasers are substantially more influential. The coefficient for the fraction of city households that are multiple-lifetime-purchasers is .128 with a t-statistic of more than 6, while the coefficient for single-purchasers users is .021 (standard error .055).

Similarly, in column 7 of Table 3 we classify computer owners into two usage groupings. We define households who report using a computer more than 20 days per month as "heavy users" and those using it fewer than 20 days per month as "light users." From this we decompose the CITY% into the share of the city that owns a computer and uses it more than 20 days per month and the share that owns but uses it fewer than 20 days per month (these average 26% and 12% of households, respectively). Again, we expect the unobserved traits of the light users to be most like the non-owners but the true spillovers to be more important from the heavy users. Again, the results show that the coefficient is much larger on the group that is less likely to share unobserved common traits (.140 on heavy users versus -.008 on light users). Indeed, the light users have no significant spillover at all.

Taken together, each of our three approaches suggests that the estimated effect of city ownership on future adoption rates is probably not caused by common unobserved traits.

VI. Identifying the Type of Network

If the CITY % coefficient is a true spillover and not just a consequence of unobserved common traits, then we would like to know more about the channel and nature of the spillover. In this section we try to determine whether local schools are an important channel, whether computer adopters are trying to keep up with the Joneses who already own computers, whether local computer retailers and the local computer industry play a special role, and whether any externalities might operate through use of e-mail and the Internet.

A. Local Schools

One explanation for the city ownership coefficient is that it is being driven by computer use in local schools. School districts in which lots of families own computers may, for example, draft curricula that encourage non-owning families to buy a computer. To see if local schools are a possible network hub, in column 1 of Table 4 we run our baseline specification only on households *without children* (hence the smaller number of observations and the absence of the children demographic control). The coefficient on city ownership is again significant and has a similar magnitude (.092 versus .102). The school system cannot directly explain the local spillovers for these households. The school system may be an important conduit of learning and network benefits of computers, but this regression suggests those benefits are not restricted to families with children in school.

B. Peer Pressure and Keeping Up With the Joneses

One possible effect of local ownership on computer adoption, distinct from conventional learning or network externality stories, arises from a desire to show off and impress others, i.e., to "keep up with the Joneses." This is certainly a type of local effect but has very different policy implications. In a world with learning from others and network benefits, it may be appropriate to subsidize adoption. If people are buying computers just to show off, in contrast, it may be appropriate to *tax* adoption.

Distinguishing "good" local influences from "bad" ones is quite difficult, but in column 2 of Table 4 we examine the computer use of people who bought their first computer in 1997. We might expect those who are buying computers just to keep up with the Joneses to use their computers less frequently once they own them. That is, if peer pressure causes our results, there might be a negative relationship between frequency of computer use by new buyers and the share of people in the city who already own computers. Higher CITY% places should have more peer pressure and more buying just for show (and thus lower use).

The results in column 2, where the dependent variable is the days per month that new buyers use their computers, indicate no significant relationship. New buyers do not use their computers less frequently if they buy in places where there are many owners.[20] The point estimate is extremely small and insignificant. The coefficient is -0.13 with a standard error of 2.05, whereas the mean use for new buyers is 23.2 days.

C. Local Prices/Local Industries

Another explanation of our local effect is that cities where there are many computer owners may have large numbers of people working in the computer industry, or they may have lower computer store prices, denser networks of computer stores, and cheaper access to the Internet. This may increase the probability of buying and thus explain our coefficient.[21] This local effect could itself arise because of network externalities. Cities with lots of computer-owning households may endogenously have a dense network of computer retailers and local phone numbers to access the Internet, benefiting new adopters.

[20] This is also contrary to what one would expect from price differences. If adoption is high because local prices are low, adopters should include more marginal buyers who will use their computer less intensively.

[21] Fixed city price differences are actually not sufficient to generate a positive correlation between the CITY% and the adoption rate of *non-owners*. For non-owners, the local market price has up to now exceeded their reservation price. If the distribution of log reservation prices across households is uniform between 0 and p (so that low price cities have higher ownership), then low price cities would need to have more rapidly falling computer prices. i.e. one would need price divergence, not just price level differences. If the distribution of reservation prices is non-uniform, however, then level differences in city prices could produce positive or negative local effects.

To test this explanation we examine the geographic areas in more detail. Thus far we have been grouping households according to metropolitan area. For each person we also have the state they live in, and many of the metropolitan areas cross state boundaries. The New York City area, for example, includes people in New Jersey and Connecticut. We therefore create a narrower local area, the "city-state". This splits a city like New York into three different city-states: New York-New York, New York-New Jersey, and New York-Connecticut. We then create the fraction of ownership within each of these city-states.

In column 3 of Table 4 we repeat our standard regression but with the ownership shares both by city-state and by city. The evidence is quite clear that the local effect is concentrated at the more local, city-state level. In column 4 we add city dummies which should absorb any metropolitan area level differences in industry composition, Internet access, computer store availability, and so on. The coefficient on the local spillover remains large, positive and significant (the coefficient is .086 with a standard error of .033). Thus the local effect cannot be explained by differences in any citywide features.[22] To explain the results, prices would have to differ systematically *within* metropolitan areas. Because of these results, in the regressions that follow we will use the CITY-ST% rather than the CITY%.

We are able to examine the issue in even greater detail using the information given by non-owners in 1997 of how likely they are to buy a computer in the next year. These same respondents were also asked how many of their family and friends own personal computers (potential answers to the latter are "all", "most", "some", "very few", and "none").

Column 5 of Table 4 shows a regression of the reported likelihood of buying on dummies for the share of friends and family that use computers, the fraction of the city-state that own computers, and our standard list of household observables (comparable to the specification with this dependent variable in column 5 of Table 2). The results show that, the

[22] A variant of the local price hypothesis is that the presence of computer owners affects adoption through the market for used computers. Cities with many owners may have lots of inexpensive or free old computers. Our data contains information for some respondents on the type of store in which they purchased their computer. Using this information we found the same spillovers from local ownership looking only at the decision to buy a new computer.

larger the fraction of family and friends that own a computer, the higher the reported likelihood of a first purchase in the next year. Going from "none" to "all" of friends and family owning computers raises the reported likelihood by .208 (the mean reported likelihood is .245). The friends and family dummies are highly significant, with t-statistics ranging from 9 to 40. Their inclusion also renders the estimated spillover at the city-state level small and insignificant. Column 6 of Table 4 shows that adding city-state dummies does not change the estimated effects of ownership by friends and family. These results suggest that the spillovers occur among friends and family members – exactly the people a household interacts with most – and are consistent with the idea that personal interactions form the basis of spillovers. For local effects such as prices to explain these results, the prices would need to be specific to the household and its friends and family.[23]

D. Internet and e-Mail Networks

In Table 5 we present a series of regressions, each of which breaks the CITY-ST% into computer users who do and do not report using their computer frequently for specific activities. If there are networks associated with sharing software files, for example, we might expect that spreadsheet or word processing computer users would have more influence on new adopters than would owners who do not use those types of software. The first 5 columns of Table 5 reveal, however, that spillovers from computer owners are equally strong from users and non-users of word processing, spreadsheets, games, graphics, and family budgeting – precisely the types of software where file sharing might be prevalent.

Column 6 shows that spillovers do not appear to be from use of home computers for work. The spillovers appear larger from those who do not use their computers to do work at home than from those who do, although the difference is not significant at the 10% level.

[23] These results could also be explained by common unobserved traits among friends and family, similarly inclined school districts of friends and family, and pressure to keep up with friends and family.

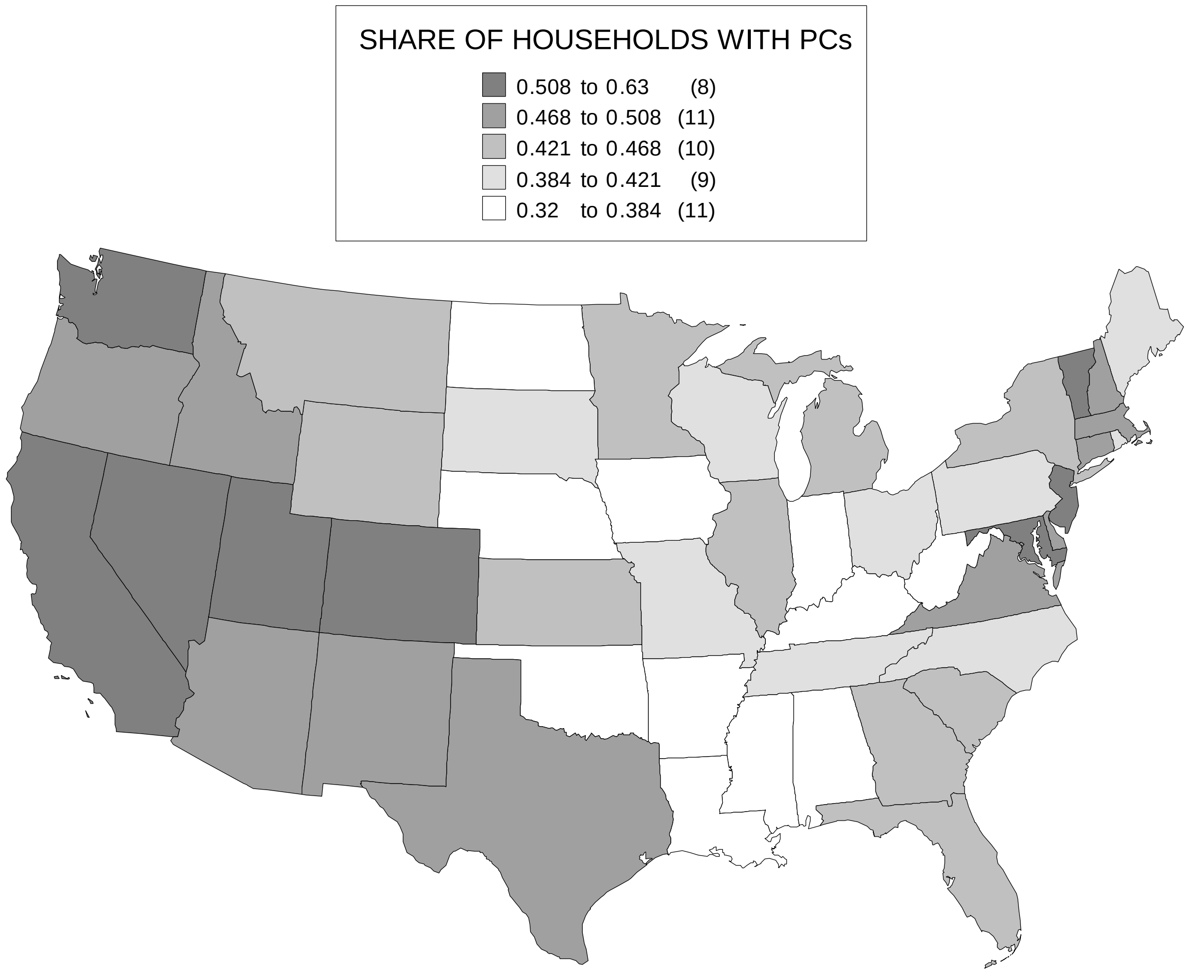
More significantly, columns 7 and 8 of Table 5 are consistent with the view that computers are components of local communication and information networks. In these columns we look at users who frequently use the Internet and e-mail. People who frequently use these are more influential. The coefficient on Internet households is .132 compared to only .044 on other households (the p-value that the coefficients are the same is .07). The coefficient on e-mail users is .141 versus .028 on those who do not use e-mail (p-value .03 on their equality). These are suggestive of local communications networks but are also consistent with local learning if Internet and e-mail users are more knowledgeable than other computer owners, or are more active in communicating with others. We do not know what share of e-mail traffic goes to local users but our data do suggest that the Internet, at least, has a strong local component. When people with on-line access are asked what they usually do on-line, the top answers do not appear particularly local (45% usually visit product or company websites and 42% usually visit reference sites), but four of the next five may include significant local content (37% check the weather, 29% read a daily newspaper, 25% usually visit a sports site, and 24% participate in on-line chats). A bigger local pool of on-line computer owners means a bigger network of local users of e-mail and, perhaps, endogenously greater supply of websites with local information.

VII. Conclusion

Using data on 110,000 U.S. households in 1997, we have found evidence that local spillovers are important for household computer adoption: households are more likely to buy their first computer when a high fraction of people around them already own computers. Our point estimates imply that such spillovers could play a quantitatively important role in the spread of home computers, perhaps doubling the rate of adoption.

Applying a battery of tests, we found that this effect was robust and unlikely to be explained by common unobserved local traits or by alternative network explanations such as local prices, local industry composition, local schools, or peer pressure. The networks do not appear to be tied to any particular type of software nor to the use of an at-home computer for work. Instead, networks seem related to use of the Internet and e-mail, consistent with computers as the hub of local information and communications networks.

Figure 1


SHARE OF HOUSEHOLDS WITH PCs
0.508 to 0.63 (8)
0.468 to 0.508 (11)
0.421 to 0.468 (10)
0.384 to 0.421 (9)
0.32 to 0.384 (11)

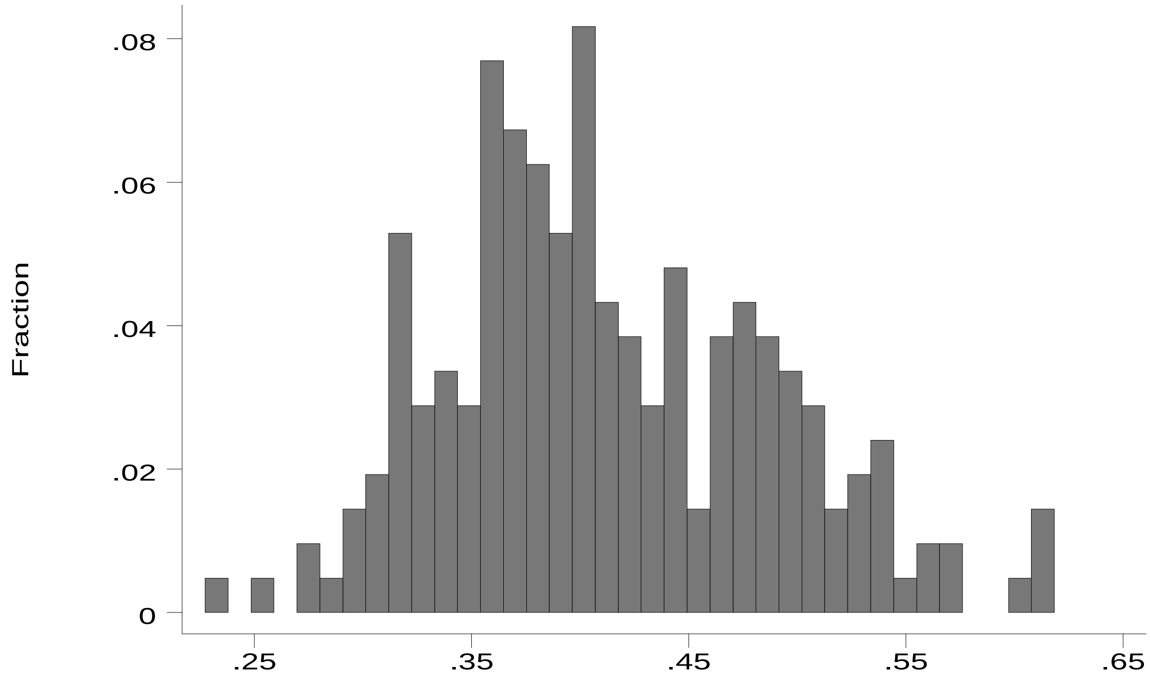


Figure 2: Mean Computer Ownership by City

TABLE 1: SUMMARY STATISTICS FOR 1997

Variable	Non-Owners	Computer Owners
Education	12.8 (2.2)	14.4 (2.4)
Income	30.0 (23.0)	52.6 (30.4)
Age	49.6 (15.4)	44.4 (13.3)
Female	.601 (.490)	.478 (.495)
Kids Age 6-17	.206 (.404)	.356 (.479)
Single	.532 (.499)	.356 (.479)
Asian	.006 (.077)	.016 (.125)
Non-Asian Minority	.137 (.344)	.102 (.303)
Use a Computer at Work	.289 (.453)	.675 (.468)
Run a Business from Home	.081 (.273)	.178 (.383)
Number of Observations	48699	60624

Notes: Standard deviations are in parentheses. Education and age are in years, income is in thousands, and the other variables are in fractions of one.

TABLE 2: BASIC RESULTS AND ROBUSTNESS

	(1) Ownership 1997	(2) Adoption 1996-97	(3) Adoption 1995-1996	(4) Adoption 1994-95	(5) Likelihood 1997-98
CITY % (year t)	.3690				
	(.0284)				
CITY % (year t-1)		.1018	.1415	.1349	.1056
		(.0154)	(.0171)	(.0183)	(.0259)
EDUCATION	.0357	.0059	.0097	.0096	.0102
	(.0009)	(.0006)	(.0005)	(.0005)	(.0006)
INCOME	.0300	.0092	.0133	.0120	.0166
	(.0009)	(.0009)	(.0005)	(.0004)	(.0006)
AGE	-.0238	-.0090	-.0056	-.0028	-.0560
	(.0012)	(.0009)	(.0008)	(.0007)	(.0010)
SINGLE	-.0785	-.0219	-.0225	-.0223	-.0104
	(.0036)	(.0024)	(.0025)	(.0024)	(.0028)
FEMALE	-.0308	-.0051	-.0047	-.0022	-.0110
	(.0026)	(.0021)	(.0023)	(.0021)	(.0026)
KIDS	.1098	.0418	.0632	.0513	.1079
	(.0052)	(.0041)	(.0027)	(.0025)	(.0042)
ASIAN	.0548	.0282	.0370	.0398	.0364
	(.0116)	(.0183)	(.0124)	(.0113)	(.0160)
NON-WHITE	-.0556	-.0122	-.0154	-.0151	.0721
	(.0051)	(.0033)	(.0032)	(.0030)	(.0059)
WORK COMP	.2113	.0701	.0667	.0639	.0816
	(.0043)	(.0032)	(.0025)	(.0024)	(.0032)
OWN BIZ	.1229	.0578	.0586	.0407	.0835
	(.0037)	(.0043)	(.0036)	(.0033)	(.0044)
N	101,253	61,399	67,599	73,433	53,468

Notes: Standard errors are in parentheses. The income and education coefficients are multiplied by 10 for presentation. Each regression is a linear probability model. Column 1 regresses ownership of the individual on the fraction of the city owning in the same year. Columns 2 through 4 regress the decision to buy a computer in the later year on the share of the city owning a computer in the previous year. Column 5 looks at the self-reported likelihood of buying a computer in the next year.

TABLE 3: CORRECTING FOR UNOBSERVABLES

	(1) OLS Baseline	(2) OLS More Controls	(3) OLS City % for Electronics	(4) IV City Means for Demog.	(5) IV Climate	(6) OLS Purchase Experience	(7) OLS Intensity Of Use
CITY %	.1018 (.0154)	.1012 (.0205)	.1039 (.0348)	.1116 (.0183)	.1625 (.0455)		
Demog.:	10 vars	10 vars	10 vars	10 vars	10 vars	10 vars	10 vars
Others:		7 goods 3 attitude vars Hrs of TV	7 goods 7 CITY% 3 attitude vars Hrs of TV				
2+ Comps CITY%						.1276 (.0201)	
1 Comp CITY%						.0213 (.0551)	
Heavy Use CITY%							.1401 (.0232)
Light Use CITY%							-.0076 (.0712)
N	61,399	38,830	38,830	61,399	61,292	61,399	61,399

Notes: Standard errors are in parentheses. Variables are defined in the text. The instruments used in the IV estimates are listed at the top of the column. Coefficients are not listed for some of the variables as indicated in each column.

TABLE 4: IDENTIFYING THE TYPE OF NETWORK

Vars.	(1) No Kids	(2) Computer Use	(3) City-States	(4) City Dummies	(5) 1998 Friends	(6) 1998 City-ST Dums
CITY %	.0919 (.0179)	-.1313 (2.050)	.0101 (.0420)			
CITY-ST %			.0926 (.0383)	.0862 (.0327)	.0340 (.0189)	
Friends w/comp--ALL					.2080 (.0101)	.2068 (.0102)
Friends w/comp--MOST					.1981 (.0047)	.1987 (.0048)
Friends w/comp--SOME					.1137 (.0046)	.1151 (.0047)
Friends w/comp--VERY FEW					.0426 (.0044)	.0444 (.0044)
Demographics: CITY Dums: CITY-ST Dums:	9 vars No No	10 vars No No	10 vars No No	10 vars Yes No	10 vars No No	10 Vars -- Yes
N	47,929	4,841	61,399	61,399	52,868	52,868

Notes: Standard errors are in parentheses. Variables are defined in the text. Column 1 restricts the sample to individuals with no children. Column 2 examines computer use measured in days per month. The dependent variable in columns 5 and 6 is the self reported likelihood of buying a computer in 1998.

TABLE 5: NETWORKS BY TYPE OF USE

Variables	(1) Word Processing	(2) Spreadsheet	(3) Games	(4) Graphics	(5) Family Budget	(6) Work at home	(7) Internet	(8) e-mail
CITY-ST% (Frequently Use Feature)	.1032 (.0173)	.0898 (.0392)	.1084 (.0307)	.0954 (.0545)	.1171 (.0436)	.0619 (.0331)	.1315 (.0198)	.1408 (.0213)
CITY-ST% (Do Not Freq. Use Feature)	.0937 (.0661)	.1125 (.0352)	.0938 (.0361)	.1048 (.0270)	.0941 (.0283)	.1498 (.0375)	.0442 (.0387)	.0283 (.0392)
Other Variables	10 Vars	10 Vars	10 Vars	10 Vars	10 Vars	10 Vars	10 Vars	10 Vars
N	61,399	61,399	61,399	61,399	61,399	61,399	61,399	61,399
p-value on equality restriction	.89	.74	.80	.90	.72	.16	.07	.03

Notes: Standard errors are in parentheses. Variables are defined in the text. Coefficients are not listed for some of the variables as indicated. The first row is the share of the city-state which owns a computer and frequently uses their computer for the purpose listed at the top of the column. The second row is the share of computer users who do not frequently use their computer for that purpose.

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