Local spillovers and learning from neighbors: Evidence from durable adoptions in rural China

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Abstract: Using the 1999 durable consumption survey data in rural China, we examine the importance of local spillovers in the diffusion of three major durable goods, i.e., color television set, washing machine, and refrigerator. We find that, with control for many family characteristics, a household is more likely to buy its first durable good in villages where a large share of households already own one. Further evidence suggests that theses patterns are unlikely to be explained by unobserved local characteristics. When examined in more detail, the extent of local spillovers appears to be negatively related to a household's knowledge about the product, and positively related to its education level. Both are consistent with the hypothesis that learning from neighbors plays an important role of these spillovers.

Keywords: Local spillovers, Social learning, Durable adoptions

JEL Classification: D12, L68

1. Introduction

When a new product is introduced to the market, potential adopters are generally concerned with its performance and reliability. Because of these uncertainties, potential adopters may postpone their purchases. These uncertainties can be effectively reduced when potential adopters are able to observe their neighbors using this new product and to know how they evaluate it. Therefore, one should expect that there be local spillovers from existing owners to new owners.[1]

The situation of rural China in the late 90s provides a unique scenario to examine the diffusion of new products. For most rural households, their adoptions of electric appliances in the late 90s were the first purchases. By examining the likelihood of durable adoptions in rural China during 1998-1999, we find that households are more likely to buy their first color television set (CTV), washing machine or refrigerator in villages where a larger share of households already own one.

However, this positive relationship may be attributed to the fact that households in the same village face similar economic environments or they have some characteristics in common. High adoption rates may reflect the existence of local durable-making firms or low local durable prices. Also, living in the same economic and social environment, neighbors may develop similar consumption preferences. This problem is pervasive in the empirical studies on network effects.[2] Using additional control variables and instrument variable (IV) estimations, we find little evidence that this positive relationship is the

[1] Network externalities may also contribute to these local spillovers. An increase in the number of users would lead to an increase in the value of a new product or lead to a development of its complementary service, thus stimulate its further adoption.

[2] See Manski (1993).

result of local common characteristics.

As Manski (2000) points out, even with finding compelling evidence that behavior is correlated within groups (here within villages), one would like to be able to say something about the reasons for this correlation. The richness of our data enables us to further examine whether these local spillovers are related to learning from neighbors. For CTV adoptions, we find that, the local spillovers are stronger for households with no TV, compared to those who have owned a similar product, a black-white television set (BWTV). We follow the differences-in-differences approach, so are able to include village dummies to maximally control for the effects of correlated common unobservables. The above evidence supports the learning hypothesis in that there should be something new to learn in the first place.[3] The social learning effect becomes less influential when potential adopters have already acquired relevant knowledge.

We further examine the interaction effect of education level and local spillovers on the likelihood of adopting these three durables, respectively. Again, village dummies are included in the regressions. We find that the strength of local spillovers is positively related to a household's education level – the better educated a household is, the more strongly the likelihood of its durable adoption is influenced by local ownership rates. This finding is consistent with the social learning hypothesis in that more educated individuals are more capable learners,[4] thus more efficient to acquire information through learning from their neighbors. In summary, our study provides evidence not only on the existence

[3] Similarly, Duflo, Kremer, and Robinson (2008) find that farmers in Kenya do not obtain information from their neighbors about fertilizer use because the existing technology at the time of study was not new.

[4] As raised by Schultz (1975), education enhances one's ability to receive, decode and understand information.

of local spillovers in the diffusion of new products, but also on that education is positively related to the extent of these spillovers.

Social learning and education level have been documented individually to stimulate new technology adoptions.[5] However, there is little evidence on how education would influence the effect of social learning. As far as we know, our study is among the first to test and provide evidence on the interaction between education and local spillovers based on the social learning hypothesis. Although what we study is on new durable adoptions, our results may shed light on new technology adoptions.[6] Given a higher complexity of new technologies, the spillovers in their diffusions might also be tied to the education level.

The interaction effect between education and social learning with respect to new technology adoption may be important to growth. A poor country can accelerate its catch-up by adopting new technologies developed in rich countries more quickly if the spillovers are stronger. Though it is unclear what the mechanism would be to induce the spillovers, social learning is a possible candidate.[7] It is likely that schooling may augment the social learning, thus accelerating the catching-up process of a poor country.

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[5] For education effects, Abdulai and Huffman (2005) find that the likelihood of a farmer in Tanzania to adopt hybrid cow technology depended positively on his education level. Lin (1991) finds similar results for the diffusion of hybrid rice in China. Foster and Rosenzweig (1996) show that whether any family member has primary education is an important predictor of a household's new farming technology adoption. By examining the adoption of four new technologies, hybrid corn, beta-blockers, tractors, and computers, across states in the U.S., Skinner and Staiger (2005) find that education and social networks are the only variables that are significant to explain the adoption rates for all these four innovations.

[6] It seems reasonable to make this extension. A new technology may be materialized as a new product, such as computer, ATM, software, and etc. A washing machine may be looked upon as a new technology to replace manual clothes-washing. With its adoption, the labor involved in washing clothes can be allocated to other production tasks.

[7] Lucas (1993) has realized the importance of social learning. He raises the following question and suggests to have it included in the growth theory, "Does learning accrue solely to the individual worker, manager, or organization that does the producing, or is some of it readily appropriable by outside observers?"

The rest of our paper is organized as follows. Section 2 reviews the related literature. Section 3 describes data. Section 4 reports empirical results. Section 5 further discusses the mechanism behind the local spillovers. Section 6 concludes with policy implications.

2. Related literature

Evidence on the learning effect has been documented among new technology and product diffusions. In his pioneering study on the diffusion of hybrid corn in the U.S., Griliches (1957) finds evidence consistent with later adopters learning from early adopters. Foster and Roserzweig (1995) and Conley and Udry (2001) find that farmers learn from each other about new technologies, especially the knowledge on detergent use associated with the new breed. Munshi (1996) finds that the network effect on new technology diffusion is due to social learning. Using a unique dataset on sunflower adoption in Mozambique, Bandiera and Rasul (2006) document that, consistent with information sharing, the network effect is stronger among farmers who report discussing agriculture with others. There is also evidence from the empirical study in health economics, labor economics and industrial organization. By examining several competing antiulcer drugs, Berndt, Pindych and Azoylary (2003) find that the network effect due to information dispersion influences consumer's choice and evaluation. Bertrand, Luttmer and Mullainathan (2000) find that information sharing influences individual participation on social welfare projects. Irwin and Klenow (1994) document the learning effect in semi-product industry. Thornton and Thompson (1998) examine the knowledge spillover in the ship building industry during the WWII.

Our paper is also related to the literature on network effects. Much of this evidence relates to technology adoption by firms, including electronic table (Church & Gandal, 1992), digital-control machine (Karshenas & Stoneman, 1993), ATM (Saloner & Shepard, 1995), etc. In contrast, studies documenting network effects among consumers are few and far between. Among the few exceptions, Gandal (1994) shows that consumers were willing to pay a premium for spreadsheet software compatible with the Lotus platform and with external database programs; Goolsbee and Klenow (2002) report that people are more likely to buy their first home computer in areas where a high fraction of households already own computers; and Park (2004) finds that network externalities in video cassette recorders explain much of the dominance of VHS relative to Betamax.

3. Data description

Data used in this paper mainly comes from an October 1999 survey of rural durable goods consumption conducted by the Rural Survey Organization (RSO), the National Bureau of Statistics (NBS) of China. We also use data from the RSO's regular annual household survey of 1998. The consumption survey covered over 20,000 households from all the Chinese continental provinces except Tibet. They were drawn by a stratified random sampling method from the RSO regular survey frame of about 68,000 households. The purchases of 16 durables were investigated.[8] We exclude from my sample the 0.7 percent of households with no power. Further removal of invalid observations leaves us with around 18,000 households.

Our focus is on three major durables, CTV, washing machine and refrigerator. We treat the purchases of these three durables in rural China during the late 1990s as first

[8] They were BWTV, CTV, washing machine, refrigerator, fan, radio recorder, camcorder, VCD player, camera, microwave, rice-cooker, air conditioner, pager, bicycle, automobile, and motorcycle.

purchases rather than replacements. When China started its reform in the early 80s, these durables were scarce even in urban area. Most rural households did not begin their purchases until the 1990s. In the survey, 97% of households reported their CTV purchases were within 10 years. This number was 91% for washing machine, and 96% for refrigerator. If the replacement cycle is around 10 years, assuming that these durable consumptions were first purchases seems reasonable.[9]

(Table 1)

Table 1 provides some summary statistics of these three durable consumptions, respectively. households are divided by their ownership status. For each durable, column (1) is for households who reported no adoption at the survey, and column (2) is for those who reported adoption since 1998. For completeness, column (3) is for those households who reported adoption before 1998. All three durable consumptions share the following characteristics. Compared to non-owners, owners were better educated, and earned higher income. As expected, these owners also enjoyed lower electricity prices, stronger television signals (for CTV), and having tap water (for washing machine). Moreover, new adopters since 1998 faced a higher village ownership rate than non-owners. In summary, the statistic summary suggests that household characteristics, public service, and lagged ownership rates may influence the adoption of these three durables.

(Figure 1)

[9] Owning more than one durable was minor. Take CTV for example. Only 3.2% of surveyed households reported the ownership of more than one CTV. They are excluded from our examination since we only have the information on the year of their latest CTV adoption. For this reason, 65 valid observations are deleted when we examine CTV adoptions. This number is 13 for washing machine, and 6 for refrigerator.

Figure 1 shows the spot and estimated linear relationship between CTV adoption rates since 1998 and the CTV ownership rates in 1997 at the county level. For those counties with higher ownership rates in 1997, their adoption rates are also higher. The OLS estimated coefficient is 0.60 (standard error is 0.05; t-value is 12.) This positive relationship also exists in washing machine and refrigerator adoptions.

4. Empirical results

4.1. Empirical specification

We analyze the local spillovers on durable diffusion using cross-sectional linear probability (LP) regressions of household purchases. We follow the convention in the literature on the demand for durable goods (e.g., Dubin and McFadden, 1984; Farrell, 1954) and treat the demand as a binary decision of buying or not. The extent of local spillovers is measured by the durable ownership rate at the village level since rural households interact with each other the most within a village. The estimation model is as follows.

$$Prob(y_{it}=1)=\lambda village\%_{t-1}+\beta x_i^0+x_i^u+u_i \text{。} \tag{1}$$

$Prob(y_{it}=1)$ is the likelihood of purchasing since year *t* for household *i*. $village\%_{t-1}$ is the village ownership rate at the end of year $t-1$.[10] Take CTV adoptions for example. We examine the likelihood of CTV adoption during the period starting at 1998 and lasting until the time of the survey. The dependent variable is a binary variable that equals one if a household purchased a CTV during this period, and zero otherwise. If

[10] Using lagged, instead of contemporaneous, ownership rates to measure local spillovers helps to mitigate the identification problem raised by Manski (1993) as the reflection problem, i.e., while a household is influenced by its neighbors' decisions, in turn, it influences their decisions as well.

there are local spillovers, with control for all other factors, non-owners in villages where owners are prevalent would be more likely to buy a CTV, that is, $\lambda > 0$.

In equation (1), x_i^0 is the vector of observed household and village characteristics. Household characteristics include net income per capita, average years of education, average age, family size and male ratio. Village characteristics include stability of the power supply (stable=1), access to a TV signal receiving tower (yes=1), TV signal strength (good=1), access to tap water (yes=1), and etc.[11] x_i^u represents the unobserved characteristics, which are correlated with $village\%_{t-1}$, but not with x_i^0. u_i are the other unobserved characteristics, including those correlated with x_i^0.

Unobserved characteristics in x_i^u may lead to estimation bias. If $village\%_{t-1}$ is positively correlated with x_i^u, its coefficient λ would be overestimated. People in coastal area are more inclined to accept new stuff. Even though they may not have CTV at the moment, their propensity to adopt one is still higher. The failure to control for this common propensity would spuriously make the estimated local spillover larger. On the other hand, if $village\%_{t-1}$ is negatively correlated with x_i^u because of survivor bias, its coefficient would be underestimated. In either case, we should need instrument variables.

4.2. Baseline estimation result

We report in column (1) of Table 2 the baseline regression on the likelihood of CTV adoption since 1998. Some villages have fewer than ten sample households in the dataset, and one might be concerned that the sample village ownership rates are imprecise

[11] Rong and Yao (2003) find that the improvement of public service provision stimulates the consumption of electric appliances in rural China.

estimates of their population means. To reduce this measurement error, we restrict my sample to villages with at least ten observations.[12] Since the ownership rates vary only at the village level, the standard errors are corrected to allow for group effects within villages.

As shown in table 2, near half of the estimates are significant at the 1% level, mostly with signs consistent with expectations. Higher income, greater average education and higher population increase a household's likelihood to adopt a CTV. The effects of average age and the male ratio are insignificant. The positive effect of income is as expected. Higher educational levels have two effects. First, people with more education tend to have a higher desire for a modern life style. Second, more education implies easier adaptation to new technologies. More family members reduce the cost per capita by sharing a CTV, which increases the household's willingness to buy.

(Table 2)

The estimated coefficient on $village\%_{t-1}$ is 0.29, significant at the 1% level. This implies that, controlling for household characteristics and public services, in a village with 10% higher CTV ownership in 1997, a non-owner's probability of making a purchase since 1998 would increase by 2.9%.

BWTV households and non-BWTV households may behave differently with respect to the decision-making to adopt a CTV. Specifically, owning a BWTV or not may influence the extent of local spillovers. Take learning effects for example. Different from non-BWTV households, BWTV households may have accumulated some knowledge

[12] We repeat the regressions with the sample of villages with at least 4 or 8 observations, respectively. The major results persist.

about CTV from their daily use of BWTV. To address this concern, we split the sample into BWTV households and non-BWTV households by whether they owned a BWTV before 1998, and estimate each separately. The results are reported in columns (2) and (3). Although the magnitude of estimated coefficients is not comparable between these two estimation results, their sign and significance are. There are three major differences. First, the age effect is positive among BWTV households; this effect turns negative for non-BWTV households. It seems that younger households are less likely to adopt a CTV if they already own a BWTV, whereas they are more likely to do so if they do not have one. Second, the effect of family size is positive among BWTV households, but insignificant among non-BWTV households. Third, the strength of TV signal stimulates CTV adoption among non-BWTV households, but not among BWTV households.

Similarly, we expect local spillovers exist in the diffusion of either washing machine or refrigerator. Columns (4) and (5) report the estimation results on the likelihood of washing machine and refrigerator adoption since 1998, respectively. The estimated coefficients on $village\%_{t-1}$ are 0.25 and 0.34, both significant at the 1% level, indicating that local spillovers persist in the diffusions of various durables.

We use the hazard function to primarily evaluate the contribution of local spillovers to the speed of durable diffusion. We use the adoption of washing machine to demonstrate. Summing up equation (1) in both sides at the village level leads to

$$\frac{f_{ct}}{1-F_{c,t-1}} = \lambda F_{c,t-1} + \beta x_c^o + x_c^u \,, \tag{2}$$

in which f_{ct} is the adoption rate of village *c* starting at year *t*, $F_{c,t-1}$ is the washing machine ownership rate in village *c* in year $t-1$. $\frac{f_{ct}}{1-F_{c,t-1}}$ therefore represents the hazard rate of CTV adoption since year *t*. Using the information in Table 1, we are able to calculate the adoption hazard since 1998, which turns out to be 4.6%.The ownership rate that a non-owner faced in 1997 is 10.2% on average. From column (4) of Table 2, we have $\lambda = 0.25$, thus $\lambda * F_{c,t-1}$=2.6%. That is, the local spillovers contribute 2.6% to the hazard rate 4.6%, $\beta x_c^o + x_c^u$ contributes the rest 2.0%. If λ accurately measures the spillovers, 57% (2.6% over 4.6%) of washing machine adoption starting at 1998 is due to the spillovers. By the same approach, we find that 31% of CTV adoptions and 56% of refrigerator adoptions since 1998 were due to local spillovers. For CTV, the contribution of local spillovers is much lower than that for other two durables. The reason may lie in that the extent of local spillovers is much lower for BWTV households than for non-BWTV households as shown in columns (2) and (3) of Table 2. We will revisit this point in the later section.

4.3. Estimation bias

An alternative explanation why the estimated coefficient on $village\%_{t-1}$ is positive is that $village\%_{t-1}$ is correlated with some unobserved common characteristics. First, living in the same economic and social environment, neighbors may develop similar consumption preferences. Second, higher ownership rates may be due to lower local price or well-developed local services. These factors would also imply that those who did not purchase would have a higher propensity to buy in the later time. We now use proxies and instrument variables to deal with these unobservables.

4.3.1. Control for unobservables

If the positive coefficient on $village\%_{t-1}$ is from the unobserved propensity to accept new stuff instead of local spillovers, adding variables that are correlated with an individual's propensity should reduce the coefficient on $village\%_{t-1}$. We add three interactions of the household characteristics (net income per capita*average years of education, net income per capita*average age, average years of education*average age) and 15 dummies for ownership of other durables at the beginning of 1998. We also add ownership rates of 12 durables in 1997 to capture the average propensity of households to adopt durables at the village level.[13] It is well known that it is hard to well control for income effects. Including the ownership status of other durables should also help in this aspect.

(Table 3)

Table 3 reports the estimation results on the likelihood of the adoption of CTV, washing machine, and refrigerator, respectively. For reference, column (1) replicates the baseline estimation results in Table 2. The additional ownership rates are calculated based on the ownership status of each household within a village. To mitigate the colinearity, we first use family ownership status and ownership rates separately, and then we pool them together. Column (2) of Table 3 adds three interactions and 15 ownership status dummies; column (3) adds three interactions and 12 ownership rates; column (4) brings in all controls. Let us first discuss CTV adoptions. For BWTV households, the

[13] For CTV adoption, the ownership rates of refrigerator, washing machine and BWTV are dropped because these are highly correlated with CTV ownership rates. For ownership rates of the rest 12 durables, their correlations with CTV ownership rates are lower than 20%.

estimated coefficient on $village\%_{t-1}$ turns insignificant with the inclusion of additional controls. This disappearance of the significance indicates that the former significance most likely comes from the failure to well control for correlated unobservables. In contrast, for non-BWTV households, the estimated coefficient on $village\%_{t-1}$ only falls slightly, and persists significantly positive. For washing machine, the change in this coefficient is negligible; for refrigerator, there is a slight drop in the coefficient. In the last three scenarios, adding controls tends to draw down the estimated coefficient on $village\%_{t-1}$, but it persists significantly positive. These make us more confident that their estimated coefficient on $village\%_{t-1}$ does not merely reflect its correlation with local unobservables.

4.3.2. Instrument variables

Our next strategy for dealing with unobservables is to use instrument variables. Instrument variables must be relevant (correlated with the village ownership rate) and valid (uncorrelated with the household's unobservables). Local spillovers imply that, conditional on its characteristics, a household should be more likely to buy its first durable if it is surrounded by households with characteristics favoring this durable ownership. For example, a low-educated household surrounded by high-educated households should be more likely to purchase than a low-educated household surrounded by low-educated households. Thus, village means as instrument variables should be relevant. We use five village means (average net income, average years of education, average age, population, male ratio) as instruments.

But are these village means (x_c^0) valid, that is, are they uncorrelated with household unobservables (x_i^u)? Note that x_c^0 is orthogonal to x_i^u by definition. x_i^u was defined as those unobserved characteristics that are correlated with $village\%_{t-1}$ conditional on a household's observed characteristics. The part of the unobservables correlated with a household's observables was included in the error term, u_i. Since observables are included in the regressions, correlation between unobservables and observables would bias the coefficients on these observables, but not the coefficient on $village\%_{t-1}$. For example, the coefficient on the education level should incorporate any correlation between a household's tendency to accept new stuff and its education level. For this reason, village means would not be correlated with x_i^u. Case and Katz (1991) develop this insight in their study on the effects of neighborhood peers on the behaviors of inner-city youths. Goolsbee and Klenow (2002) apply this approach to examine the importance of local spillovers in the diffusion of home computers. Duflo and Saez (2002) also use this strategy when they examine individuals' decisions about whether to enroll in a university-sponsored retirement plan. Admittedly, this instrument may still be invalid if there is a correlation between village means and the household's unobserved propensity to adopt a new product even after controlling for its family characteristics.

(Table 4)

Table 4 reports the instrument estimation results for CTV, washing machine and refrigerator, respectively.[14] Since we have ruled out the existence of network effects

[14] We test the validity of our instruments. Take CTV for instance. In the first-stage regression, village means explain the variation of village CTV ownership rates by 15% (R^2 =0.15). Moreover, we cannot reject the four overidentifying restrictions at the five percent level (R^2 =0.00; nR^2 =0.00; less than the 5%

among BWTV households for CTV adoption, we only perform IV estimation among non-BWTV households. Since the validity of this IV estimation also relies on how well correlated unobservables are controlled for, we take the estimation of column (4) in Table 3 as the baseline. For reference, column (1) replicates the baseline estimation result. In column (2), we include all five village means as instruments. In column (3), we drop the village mean population and male ratio from the instrument set. In column (4), we only include the village means of average net income and average years of education in the instrument set. For CTV or refrigerator adoption, the estimated coefficient on $village\%_{t-1}$ becomes larger, and persists significant. For washing machine, its estimated coefficient drops, and the significance turns marginal. The increase in the coefficient when using instruments may be due to survivor bias (Heckman and Singer, 1985). For example, the only household who does not own a CTV given that everyone else in its village have owned one actually hates CTV. This would lead to a downward bias in the baseline regression. With instrument, this survivor bias is avoided, thus the estimated coefficient on $village\%_{t-1}$ increases. It is unclear why this survivor bias does not influence the IV estimation of washing machine adoption in the similar way. To summarize, for CTV and refrigerator adoptions, the results of instrument estimations indicate that unobservables are unlikely the main reason of getting the positive estimated coefficient on $village\%_{t-1}$.

5. Learning effect

If the *village%* coefficient comes from local spillovers, one would like to know more about the channel of these spillovers. In this section, we try to determine whether

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value of the χ_4^2 distribution.). For washing machine and refrigerator, village means as instruments also pass the tests mentioned above.

households with similar products are less influenced than others and whether education level plays a role.

5.1. BWTV purchases

If social learning is the reason behind the positive coefficient on $village\%_{t-1}$, those households who are less familiar with the new product should be influenced by local spillovers more strongly. The uniqueness of CTV adoption is that a household may have had a BWTV when he makes the decision to buy a CTV.[15] A BWTV functions similarly to a CTV. Through daily use, BWTV households should have developed some idea about how a CTV should work. Therefore, having a BWTV is a good proxy indicating that a household has better knowledge about CTV compared to those who do not have one. The social learning hypothesis implies that, with better knowledge, its CTV adoption decision should tend to be less influenced by the CTV purchases of its neighbors. In contrast, if local spillovers exist due to peer pressure or because of households simply imitating their neighbors, we should not expect much difference between these two groups. The estimation results are reported in Table 5. In column (1), we introduce a dummy indicating a household owned a BWTV before 1998, and its interaction term with CTV ownership rates, "$village\%_{t-1}$*having a BWTV". This interaction measures how the effect of ownership rates differs between non-BWTV households and BWTV households. Because our focus is on the interaction term, we are essentially utilizing the differences-

[15] The survey data provides the information on whether a household had a BWTV at the survey time and the purchasing year if having one. It would not report if a household had owned a BWTV but had disposed it after having a CTV. Therefore, using the "having a BWTV" dummy would lead to estimation bias. To minimize this error, we also regress the likelihood of CTV adoption since 1999 rather than 1998. The main results persist. Note that the measure bias and the hypothesis point to the opposite direction. Therefore, the fact that we still get the expected result even with the measure bias is a support to the hypothesis that learning effects did exist.

in-differences approach. This methodology allows us to control for local common unobservables down to the village level by including village dummies. This eliminates many of the unobservable biases, which is essential to the identification of network effects.[16] In China, a village is of small size, with about 250 households for a typical one. As shown, the estimated coefficient on "$village\%_{t-1}$ *having a BWTV" is -0.35, significant at the 1% level. This implies that, given everything else equal, when CTV ownership rates increase by 10%, the likelihood of adopting a CTV for a non-BWTV household would increase by 3.5% compared to a BWTV household. Therefore, our estimation results support the learning hypothesis that BWTV households had better knowledge on CTV than non-BWTV households, thus were less influenced by the CTV ownership status of their neighbors. Meanwhile, these results reject the hypothesis that local spillovers mainly come from peer pressure or simple imitation.

(Table 5)

Notice that our estimation results are not due to the fact that non-BWTV households have a higher propensity to purchase CTV than BWTV households because we have controlled for this effect by including the "having a BWTV" dummy. To further rule out the possibility that our results are due to the substitution effect of BWTV to CTV, we test the following implication from the substitution hypothesis. The longer the use of a BWTV, the more likely it would trigger an upgrade by adopting a CTV. If our results are due to knowledge about CTV during the process of using a BWTV, the holding period, once long enough, should have little influence on the estimated coefficient on $village\%_{t-1}$. We repeat the estimation of column (1) with including the dummy of indicating that a

[16] Bertrand, Luttmer and Mullainathan (2000) follow a similar approach.

household had owned a BWTV for more than five years and more than ten years, and report the results in columns (2) and (3), respectively. "$village\%_{t-1}$ *having a BWTV" now measures how the effect of ownership rates differs between non-BWTV households and households who owned a BWTV less than five years (for column 3, it switches to ten year); "$village\%_{t-1}$ *having a BWTV*owning more than five years" measures how the effect of ownership rates varies among households with BWTV more than five years and households with one less than five years (ten years for column 3). In either column (2) or column (3), the estimated coefficient on the last interaction term is insignificant, indicating that the holding length of a BWTV has no significant influence on our estimation results. Therefore, we further confirm that the positive coefficient on $village\%_{t-1}$ is unlikely due to the substitution effect of BWTV.

5.2. Education level

Would the education level make a difference on these local spillovers? Generally speaking, people with higher education level have higher learning capabilities. Therefore, based on the learning hypothesis, we should expect that households with higher education level should be more efficient to learn from their neighbors, thus more likely to take full advantage of this information convenience.[17] To test this implication, we add the interaction term "$village\%_{t-1}$ * average years of education" to the baseline regression.

[17] Rather than being a complementary good to learning from neighbors, the education level may be a substitute. Including learning from neighbors, there are other channels, such as reading books, to acquire related information. A person with higher education may have easier access to other channels, which makes him rely less on learning from neighbors. However, given the convenience (low cost) and the high efficiency of learning from neighbors, we expect that the substitution effect of education should be weak, thus its complementary effect should dominate. Moreover, with the presence of substitution effects, finding a positive relationship between the education level and local spillovers would be a support to the hypothesis that the complement effects did exist.

Social learning implies its coefficient should be positive. Again, we include village dummies.

(Table 6)

In column (1) of Table 6, we run the regression, restricting the sample to non-BWTV households. The estimated coefficient on "$village\%_{t-1}$ * average education year" is 0.05, significant at the 1% level. This indicates that households with higher education level are more strongly influenced by CTV ownership rates. In column (2), we regress among BWTV households. The estimated coefficient on "$village\%_{t-1}$ *average education years" turns insignificant. It seems that households did accumulate knowledge about CTV based on their daily use of BWTV; thus, learning capabilities made little difference among households with BWTV. This also explains our previous finding that the contribution of local spillovers to the diffusion speed of CTV is much lower than the other two durables. In columns (3) and (4), we run similar regressions for washing machine and refrigerator adoption, respectively. The estimated coefficient on "$village\%_{t-1}$ *average education years" persists significantly positive in either case.

For robustness check, we use another measure of education to replace average education years. It is the schooling of the household head. In the survey, the education status of the household head can take five different values. Level 1 corresponds to illiterate, level 2 to primary school, level 3 to junior high school, level 4 to senior high school and level 5 to higher education. Schooling is defined as the school years of the household head. Using the terminology of China's education system, illiterate corresponds to 0 years in school, primary school to 6 years in school, junior high school to 9 years in school, senior high school to 12 years in school, and higher education to 14 years in school. We repeat the regressions and report them in columns (5) to (8) of Table 6. The major results persist. Therefore, we further confirm that the effect of learning capabilities to local spillovers in the diffusions of these three durables.

The education effects on social learning may be non-linear. For example, it may be the case that literacy is essential to learn from neighbors; once above this level, additional education makes little contribution. To test this non-linearity, we replace the education measure by dummies indicating a household head is at certain education level. The default is illiterate. With the inclusion of 4 dummies and their interactions with $village\%_{t-1}$, we repeat the estimations and report in columns (9) to (12). In general, the estimated coefficient on each interaction is significantly positive, indicating that households with higher education are influenced more strongly by local spillovers, compared to a typical illiterate household. However, we don't observe the pattern that the coefficients on interactions increase over education. This confirms our non-linear concern. More specifically, once the literacy capability is developed, further schooling makes little difference on the efficiency in this type of social learning. Different from other interactions terms, the significance of the coefficient on "$village\%_{t-1}$*associate dummy" is volatile across estimations. For washing machine and refrigerator, the head holding an associate or above degree makes the likelihood of adoption more strongly influenced by local spillovers, compared to other lower education level. However, for CTV, the estimated coefficient on "$village\%_{t-1}$*associate dummy" is insignificant. We only speculate that associate heads have accumulated some knowledge about CTV even without BWTV.

6. Conclusions

Using the 1999 durable consumption survey data in rural China, we examined the importance of the role of local spillovers – including learning and network externalities – in durable consumption. We found that, with control for family characteristics, households are more likely to buy their first CTV, washing machine or refrigerator in villages where a large share of households already own one. In addition, for non-BWTV households, this local spillover is significantly positive; however, for BWTV households, this effect is insignificant. Furthermore, with the examination of the likelihood of adopting three durables, respectively, we found that the extent of local spillovers is positively related to the education level of households. The latest two findings are consistent with the hypothesis that the local spillover involves learning from neighbors.

As far as policy implications are concerned, the effect of public policies would be amplified by the local spillovers. This phenomenon is called the "social multiplier" by Becker and Murphy (2000). Not long ago, the Chinese government launched a series of subsidy policies to stimulate domestic, especially rural, consumption on durables. Such policies include "bringing electric appliances into rural families (*jiadian xiaxiang*)", "bringing construction material into rural families (*jiancai xiaxiang*)", and subsidizing the energy efficient electric appliances. The local spillovers imply that these subsidies would not only stimulate those who do purchase, they would also stimulate the adoption of potential consumers indirectly. Even after the termination of these policies, their stimulating effects will last for a long time because of the local spillover. Based on our research, the local spillovers should be stronger in the diffusion of new products. Therefore, the subsidy policy would be more influential if it focuses on the appliances that are less popular in rural area (such as air conditioner, computer, and LCD TV). Similarly, subsidizing energy-efficient appliances should also have long-term stimulating effects.

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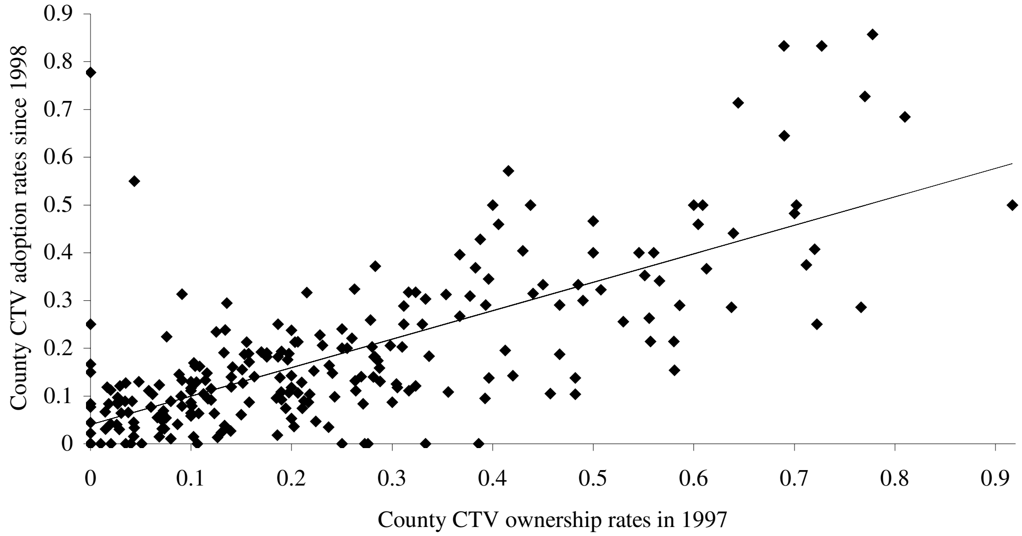

Fig. 1. County CTV Adoption Rate since 1998.

Table 1

Summary statistics of owners and non-owners.

Variable	CTV			Washing Machine			Refrigerator		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Village ownership rate in 1997	0.14	0.26	0.53	0.09	0.31	0.59	0.04	0.22	0.50
	(0.18)	(0.23)	(0.26)	(0.17)	(0.25)	(0.26)	(0.10)	(0.24)	(0.30)
Average net income (1,000 yuan)	1.92	2.70	2.83	2.02	2.77	2.98	2.08	3.51	3.87
	(1.29)	(1.85)	(1.95)	(1.42)	(1.86)	(2.03)	(1.42)	(2.39)	(2.35)
Average years of education	5.43	6.03	6.13	5.49	6.24	6.33	5.59	6.41	6.64
	(1.92)	(1.84)	(1.85)	(1.93)	(1.78)	(1.83)	(1.91)	(1.80)	(1.87)
Average age (100 years)	0.32	0.33	0.33	0.32	0.33	0.32	0.32	0.33	0.35
	(0.11)	(0.09)	(0.10)	(0.11)	(0.09)	(0.09)	(0.10)	(0.09)	(0.10)
Population	4.27	4.15	4.23	4.26	4.19	4.14	4.25	4.12	4.01
	(1.22)	(1.19)	(1.25)	(1.23)	(1.20)	(1.19)	(1.22)	(1.28)	(1.24)
Fraction male	0.52	0.54	0.52	0.52	0.54	0.52	0.52	0.54	0.53
	(0.22)	(0.22)	(0.21)	(0.22)	(0.21)	(0.21)	(0.22)	(0.22)	(0.22)
Electricity price (yuan/kWh)	0.81	0.74	0.70	0.79	0.69	0.63	0.77	0.66	0.60
	(0.29)	(0.25)	(0.27)	(0.27)	(0.21)	(0.19)	(0.26)	(0.24)	(0.2)
Fraction in town	0.02	0.03	0.04	0.02	0.03	0.04	0.02	0.03	0.06
Fraction in rural village	0.94	0.91	0.86	0.92	0.89	0.85	0.92	0.86	0.82
Fraction with stable electricity	0.91	0.95	0.96	0.92	0.96	0.96	0.92	0.94	0.98
Fraction with strong TV signal	0.85	0.90	0.93						
Fraction with TV tower	0.11	0.10	0.11						
Fraction with tap water				0.27	0.46	0.55			
Observations	8430	1491	3384	9754	470	2486	11692	293	954

Note. Standard deviations are in parentheses.

Table 2

LP estimation results on durable adoptions since 1998.

Variable	CTV	CTV BWTV	CTV Non-BWTV	Washing Machine	Refrigerator
	(1)	(2)	(3)	(4)	(5)
village$\%_{t-1}$	0.285***	0.076***	0.544***	0.249***	0.336***
	(0.027)	(0.022)	(0.066)	(0.022)	(0.038)
Average net income	0.041***	0.037***	0.076***	0.012***	0.010***
	(0.004)	(0.004)	(0.008)	(0.002)	(0.002)
Average years of education	0.009***	0.005**	0.040***	0.004***	0.002***
	(0.002)	(0.002)	(0.006)	(0.001)	(0.001)
Average age	-0.004	0.120***	-0.229**	-0.035*	-0.009
	(0.032)	(0.029)	(0.092)	(0.019)	(0.014)
Population	0.016***	0.021***	0.002	0.008***	0.006***
	(0.004)	(0.003)	(0.010)	(0.002)	(0.002)
Fraction male	0.006	0.042**	-0.034	0.019*	0.009
	(0.019)	(0.019)	(0.056)	(0.010)	(0.008)
Town dummy	-0.015	-0.054*	0.019	-0.016	-0.008
	(0.046)	(0.028)	(0.111)	(0.021)	(0.018)
Rural village dummy	-0.021	-0.014	0.004	-0.007	-0.006
	(0.021)	(0.017)	(0.059)	(0.013)	(0.008)
Electricity stability	0.015	0.021*	0.034	0.005	-0.009**
	(0.013)	(0.011)	(0.035)	(0.006)	(0.005)
Electricity price	-0.075***	-0.032***	-0.190***	-0.023***	-0.016***
	(0.015)	(0.011)	(0.044)	(0.008)	(0.006)
Strength of TV signal	0.010	0.001	0.107***		
	(0.011)	(0.010)	(0.032)		
Having TV tower	0.013	0.007	-0.034		
	(0.014)	(0.012)	(0.034)		
Having tap water				0.008	
				(0.007)	
Observations	9863	6888	1940	10214	11982
Adjusted R^2	0.069	0.047	0.226	0.066	0.078

Note. *, **, ***: Coefficient different from zero at 10, 5, 1 percent significance levels, respectively. Standard errors are in parentheses.

Table 3
More controls for unobservables.

Variable		(1)	(2)	(3)	(4)
Having other durables		Baseline	Y	N	Y
Other durable ownership rates			N	Y	Y
CTV BWTV	$village\%_{t-1}$	0.076***	0.035	-0.004	-0.006
		(0.022)	(0.022)	(0.023)	(0.023)
	Observations	6888	6243	6301	6243
	Adjusted R^2	0.047	0.082	0.066	0.090
CTV Non-BWTV	$village\%_{t-1}$	0.544***	0.407***	0.445***	0.459***
		(0.066)	(0.068)	(0.075)	(0.076)
	Observations	1940	1725	1921	1725
	Adjusted R^2	0.226	0.273	0.235	0.279
Washing Machine	$village\%_{t-1}$	0.249***	0.232***	0.259***	0.262***
		(0.022)	(0.023)	(0.024)	(0.025)
	Observations	10214	8825	9535	8825
	Adjusted R^2	0.066	0.084	0.067	0.090
Refrigerator	$village\%_{t-1}$	0.336***	0.317***	0.305***	0.309***
		(0.038)	(0.039)	(0.042)	(0.043)
	Observations	11982	10399	11171	10399
	Adjusted R^2	0.078	0.085	0.082	0.088

Note. *, **, ***: Coefficient different from zero at 10, 5, 1 percent significance levels, respectively. Household characteristics and village characteristics are included.

Table 4
IV estimations.

		IV: Village means		
	Baseline	IV 5 village means	IV Deleting population and fraction male	IV Deleting average age, population, and fraction mal
	(1)	(2)	(3)	(4)
$village\%_{t-1}$	0.459***	1.671***	1.720***	2.008***
CTV (Non-BWTV)	(0.076)	(0.518)	(0.535)	(0.589)
Observations	1725	1725	1725	1725
$village\%_{t-1}$	0.262***	0.149	0.126	0.152
Washing Machine	(0.025)	(0.147)	(0.146)	(0.145)
Observations	8825	8825	8825	8825
$village\%_{t-1}$	0.309***	0.515***	0.445**	0.549*
Refrigerator	(0.043)	(0.196)	(0.208)	(0.294)
Observations	10399	10399	10399	10399

Note. *, **, ***: Coefficient different from zero at 10, 5, 1 percent significance levels, respectively. Standard errors are in parentheses. Household characteristics and village characteristics are included.

Table 5
The interaction effects with having a BWTV or not.

Variable	CTV		
	(1)	(2)	(3)
Having a BWTV	-0.349***	-0.349***	-0.349***
	(0.019)	(0.019)	(0.019)
$village\%_{t-1}$ * Having a BWTV	-0.315***	-0.334***	-0.325***
	(0.046)	(0.060)	(0.046)
$village\%_{t-1}$ * Having a BWTV		0.025	
*More than 5 years		(0.047)	
$village\%_{t-1}$ * Having a BWTV			0.048
*More than 10 years			(0.045)
Observations	8828	8828	8828
Adjusted R^2	0.334	0.334	0.334

Note. *, **, ***: Coefficient different from zero at 10, 5, 1 percent significance levels, respectively. Standard errors are in parentheses. For all regressions, village dummies are included.

Table 6
The interaction effects with education level.

Variable	CTV No-BWTV	CTV BWTV	Washing Machine	Refrigerator
	(1)	(2)	(3)	(4)
$village\%_{t-1}$ *Average education years	0.044*** (0.016)	-0.004 (0.006)	0.026*** (0.007)	0.043*** (0.012)
Observations	1940	6888	10214	11982
Adjusted R^2	0.389	0.120	0.174	0.183
	(5)	(6)	(7)	(8)
$village\%_{t-1}$ *Education years of the head	0.033*** (0.013)	-0.001 (0.005)	0.018*** (0.005)	0.020*** (0.007)
Observations	1940	6888	10214	11982
Adjusted R^2	0.386	0.120	0.172	0.179
	(9)	(10)	(11)	(12)
$village\%_{t-1}$ *Elementary dummy	0.283* (0.146)	0.012 (0.052)	0.145*** (0.054)	0.319*** (0.091)
$village\%_{t-1}$ *Junior high dummy	0.338** (0.150)	-0.014 (0.044)	0.174*** (0.056)	0.193** (0.075)
$village\%_{t-1}$ *Senior high dummy	0.331** (0.159)	-0.021 (0.071)	0.169** (0.073)	0.247** (0.110)
$village\%_{t-1}$ *Associate dummy	-0.023 (1.040)	-0.074 (0.323)	0.899* (0.461)	0.717* (0.372)
Observations	1940	6888	10214	11982
Adjusted R^2	0.385	0.120	0.173	0.182

Note. *, **, ***: Coefficient different from zero at 10, 5, 1 percent significance levels, respectively. Standard errors are in parentheses. For all regressions, village dummies are included.