Local spillovers and durable adoption: Evidence from durable consumptions in rural China

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Abstract
Purpose – The effects of social learning and network externalities in the diffusion of a new product imply that there should be local spillovers from existing owners to new adopters in a closely-related community. Using the 1999 durable consumption survey data in rural China, this paper examines the importance of local spillovers in the diffusion of two major durable goods, washing machine and refrigerator.
Design/methodology/approach – Based on an October 1999 survey of rural durable goods consumption conducted by the National Bureau of Statistics (NBS) of China, the authors examine the likelihood of rural households adopting a washing machine and a refrigerator during 1998-1999, respectively.
Findings – The estimation results indicate that 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 these patterns are unlikely to be explained by unobserved local characteristics. When examined in more detail, the extent of local spillovers appears to be positively related to household education level.
Originality/value – Our study reveals the importance of local spillovers in the diffusion of these two durables. Specifically, 64% of washing machine adoptions starting at 1998 are due to the spillovers. For refrigerator adoptions, this percentage is 55%. Furthermore, as far as we know, our study is among the first to test and provide evidence on the interaction between education level and local spillovers based on the learning hypothesis.
Keywords China, Rural households, Local spillovers, Durable adoptions, Washing machine, Refrigerator, Education level
JEL codes D12, L68, O33
Paper type Research paper

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.[1] On the other hand, 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. Therefore, one should expect that there be local spillovers from existing owners to new adopters in a closely-related community.

In this paper, we empirically examine the importance of these local spillovers in the diffusion of two durable goods, washing machine and refrigerator, in rural China. Our study has important implications for policy makers in China, who recently have been trying to stimulate domestic consumption with special attention to durable consumption in rural areas. Moreover, since a new technology may be materialized as a new product, the diffusion of these two durables may shed light on new technology adoptions which play a central role in the theories of development and economic growth (Grossman and Helpman, 1991).

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 washing machine (hereafter WM) or refrigerator in villages where a larger share of households already own one.

However, these detected local spillovers may be attributed to the fact that households in the same village have some unobserved characteristics in common. 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] Thanks to the richness of the data, we are able to use additional control variables, including the ownership status of other 15 durables and their village ownership rates, and we also perform instrument variable (IV) estimations. We find little evidence that this positive relationship is the result of local common characteristics. Furthermore, this spillover effect is also economically significant. Our estimation indicates that 64% of WM adoptions starting at 1998 is due to the spillovers; for refrigerator adoptions, this percentage is 55%.

Local spillovers and education level have been documented individually to stimulate new technology adoptions.[3] However, there is little evidence on how these two effects interact with each other. We examine their interaction effect on the likelihood of adopting these two durables, respectively. 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 learning hypothesis in that more educated individuals are more capable learners. Therefore, they are more efficient to acquire information through learning from their neighbors and more capable to "receive, decode and understand" information around them (Schultz, 1975).

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 learning hypothesis. Although what we study is on new durable adoptions, our results may shed light on new technology adoptions.[4] Given a higher complexity of new technologies, it seems reasonable to expect that the extent of local spillovers should also associate with the education level.

Our paper is closely related to the literature on network externalities[5]. 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.

Our paper is also related to the literature on durable consumption in China. Hu, Li and Wei (1989) are among the first to quantitatively analyze durable goods consumption in China. Rong and Yao (2003) find that the improvement of public service provision stimulates the consumption of electric appliances in rural China. Gan, Yin and Zang (2010) investigate how the privatization of public housing in the 1990s influenced durable consumption in urban China. Ying and Du (2012) document that rural households with medical insurance are more likely to adopt durables. However, local spillovers in the diffusion of durables are rarely examined. One exception is Rong (2011). By examining the consumption of color television sets in rural China, Rong (2011) documents the existence of a type of local spillovers – free riding across neighbors, which reduces the adoption propensity of non-owners.

The rest of our paper is organized as follows. Section 2 describes data. Section 3 reports empirical results. Section 4 concludes with policy implications.

2. 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.[6] 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 two major durables, WM and refrigerator.[7] We treat the purchases of these two durables in rural China during the late 1990s as first 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, 91% of households reported their WM purchases were within 10 years. This number was 96% for refrigerator. If the replacement cycle is around 10 years, assuming that these durable consumptions were first purchases seems reasonable.[8]

(Table 1)

Table 1 provides some summary statistics of these two durable consumptions, respectively. Since our estimations are restricted to villages with at least ten sample households, for consistency we impose the same restriction when calculating the summary statistics. Sample households thus reduce from around 18,000 to 12,000. 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. The population refers to the number of household members who are permanent residents (*Changzhu Renkou*). Average years of education, average age, and average net income all refer to those of permanent residents. Both 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, more stable power supply, and having tap water (for WM). Moreover, new adopters since 1998 faced a higher village ownership rate than non-owners. The statistic summary suggests that household characteristics, public services, and lagged ownership rates may influence the adoption of these durables.

(Figure 1)

Figure 1 shows the spot and estimated linear relationship between WM adoption rates since 1998 and the WM ownership rates in 1997 at the county level. For those counties with higher ownership rates in 1997, their later adoption rates are also higher. The OLS estimated coefficient is 0.29 (standard error is 0.03; t-value is 9.2.) This positive relationship also exists in refrigerator adoptions.

3. Empirical results

3.1. 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.

$$Prob(y_{i,t}=1)=\lambda village\%_{t-1}+x^{0}_{i,t-1}\beta_1+x^{u}_{i,t-1}\beta_2+u_{i,t} \qquad (t=1998), \qquad (1)$$

where $Prob(y_{i,t}=1)$ is the likelihood of purchasing since year *t* for household *i*; $village\%_{t-1}$ is the village ownership rate at the end of year $t-1$.[9] Take WM adoptions for example. We examine the likelihood of WM 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 WM during this period, and zero otherwise. If there are local spillovers, with control for all other factors, the likelihood of non-owners to buy a WM, $Prob(y_{i,t}=1)$, should be higher ($\lambda > 0$) in villages with higher ownership rates, $village\%_{t-1}$.

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 tap water (yes=1), electricity price, and location (town, suburban village or rural village). 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 things and ideas. Even though they may not have a WM 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.

3.2. Baseline estimation result

We report in column (1) of Table 2 the baseline regression on the likelihood of WM 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 estimates of their population means. To reduce this measurement error, we restrict my sample to villages with at least ten observations.[10] Since the ownership rates vary only at the village level, the standard errors are corrected to allow for group effects within villages. County dummies are included to control for common unobservables at the county level.

As shown in table 2, most estimates of household characteristics are significant at the 1% level, with signs consistent with expectations. Higher income, greater average education and higher population increase a household's likelihood to adopt a WM. The effect of the male ratio is positive, indicating a household with more male has a higher propensity to purchase a WM. It sounds reasonable given that clothes were hand-washed by the female in general. 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 WM, which increases the household's willingness to buy.

(Table 2)

The estimated coefficient on $village\%_{t-1}$ is 0.15, significant at the 1% level. This implies that, controlling for household characteristics and public service provisions, for a household in a village with 10% higher WM ownership in 1997, the probability of making a purchase since 1998 would increase by 1.5%.

We also expect local spillovers exist in the diffusion of refrigerator. Column (2) reports the estimation result on the likelihood of refrigerator adoption since 1998. The estimated coefficient on $village\%_{t-1}$ is 0.20, significant at the 1% level, indicating that local spillovers persist in the diffusions of both durables.

We use the hazard function to primarily evaluate the contribution of local spillovers to the speed of durable diffusion. We use WM adoptions 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 WM adoption rate of village *c* starting at year *t*, $F_{c,t-1}$ is the WM ownership rate in village *c* in year $t-1$. $\frac{f_{ct}}{1-F_{c,t-1}}$ therefore represents the hazard rate of WM 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 4.55% (=470/(470+9754)). That is, among every 100 households who did not own a WM before 1998, on average 4.55 households adopted one since 1998 till the survey time. The ownership rate that a non-owner faced in 1997 is 19.56% on average. From column (1) of Table 2, we have $\lambda = 0.15$, thus $\lambda * F_{c,t-1}$=2.91%. That is, the local spillovers contribute 2.91% to the hazard rate 4.55%, $\beta x_c^o + x_c^u$ contributes the rest 1.64%. If λ accurately measures the spillovers, 64% (2.91% over 4.55%) of WM adoption starting at 1998 is due to the spillovers. Similarly, we find that 55% of refrigerator adoption starting at 1998 is due to the spillovers.

To address the concern that the LP specification might potentially distort the estimation results (Long, 1997), suppose that the true model is a logit. By using a LP model instead, the ownership rate might be a proxy for the non-linear terms of other control variables, thus generating spurious coefficients. We estimate the probit and logit models, respectively. The estimated coefficient on $village\%_{t-1}$ persists significantly positive though the number of observations becomes smaller. We also repeat the regressions with county dummies replaced by province dummies. For all the three specifications, the effect of $village\%_{t-1}$ persists significantly positive while the number of observations remains the same.[11]

3.3. 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.

3.3.1. 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 end of 1997. We also add ownership rates of these 15 durables in 1997 to capture the average propensity of households to adopt durables at the village level. 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 WM and refrigerator adoption, 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

15 ownership rates; column (4) brings in all controls. For WM, the change in the coefficient on $village\%_{t-1}$ is negligible; for refrigerator, there is a slight drop in the coefficient; in both case, the coefficient persists significantly positive. These make us more confident that the estimated coefficient on $village\%_{t-1}$ does not merely reflect its correlation with local unobservables.

3.3.2. 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)

Although the above discussion suggests potential gains from IV estimations, we need to check the validity and quality of the instruments. First, the endogeneity test of Hausman (1978) is conducted by examining whether the OLS estimates are different from IV estimates. Because the Durbin-Wu-Hausman test uses the device of augmented regressors, it produces a robust F-statistic (Davidson, 2000). As shown in Table 4, for refrigerator adoptions the F-statistics indicate that IV estimates are significantly different from OLS estimates at the ten percent level. In contrast, for WM adoptions this difference is insignificant, indicating mis-specification might not be a concern when OLS estimations are used. Second, we conduct the overidentification test (Ruud, 2000) to examine whether the orthogonality condition between the instruments and the error term holds. The Sargan chi-square statistics for this test are presented in Table 4. We cannot reject the null hypothesis that the orthogonality condition holds, except for the situation when five village means are used as instruments in the estimation of refrigerator adoptions. In this case, we take cautions when using these five village means as instruments. Third, we perform the weak instrument test to determine whether the instruments are sufficiently correlated with the endogenous regressor. Stock and Yogo (2005) propose the test statistic, which is the F-statistic for joint significance of instruments in the first-stage regression. As shown in Table 4, the F-statistic for each case indicates that our instruments are strong.[12]

Table 4 reports the instrument estimation results for WM and refrigerator adoption, respectively. For reference, column (1) replicates the baseline estimation results in Table 2. 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. According to the literature, village means of variables are calculated based on sample households in the village, with the examined household excluded.

For WM adoption, the estimated coefficient on $village\%_{t-1}$ becomes larger whereas the significance turns marginal (still significant at the 20% level). For refrigerator, the magnitude of the coefficient rises by three times, and the significance persists. This increase when using instruments may be due to survivor bias (Heckman and Singer, 1985). For example, the only household who does not own a WM given that everyone else in its village has owned one actually hates WM. 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 WM adoption in the similar way. To summarize, for WM and refrigerator adoptions, the results of instrument estimations indicate that unobservables are unlikely the main reason of getting the positive estimated coefficient on $village\%_{t-1}$.

3.4. The interaction between education and local spillovers

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 and more capable to "receive, decode and understand" information around them, thus more likely to react to this spillover.[13] To test this implication, we add the interaction term "$village\%_{t-1}$ * average years of education" to the baseline regression and expect its coefficient to be positive. Doing so enables us to add village dummies.

(Table 5)

In column (1) of Table 5, we run the regression of WM adoption. The estimated coefficient on "$village\%_{t-1}$ * average years of education" is 0.026, significant at the 1% level. This indicates that households with higher education level are more strongly influenced by WM ownership rates. In column (4), we run the similar regression for refrigerator adoption. The interaction effect persists significantly positive.

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 (2) and (5) of Table 5. The major results persist. Therefore, we further confirm that the interaction effect of education and learning capabilities on local spillovers in the diffusions of these two durables.

The education effects on local spillovers 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 in columns (3) and (6). 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 below the associate degree. This confirms our non-linear concern. More specifically, once the literacy capability is developed, further schooling below the associate degree makes little difference on the efficiency in this type of learning. 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. It seems that having the associate degree or above makes individual more capable to capture changes around them and more adaptive to follow the new trend. Since collages are located in cities, we speculate that the experience living in cities may help in this aspect.

4. 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 further found that the extent of local spillovers is positively related to the education level of households, indicating individual's learning ability influences the extent of local spillovers.

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 existence of local spillovers implies 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. Specifically, our research indicates that these local spillovers should be stronger in the diffusion of new products. Therefore, for electric appliances that are popular and the adoptions of which are mainly replacements, the subsidy policy would be less influential. In contrast, it would be more influential for the appliances that are less popular in rural area, such as air conditioner, computer, and car. Moreover, due to regional income inequality, the ownership rates vary across rural China. It is possible that the adoptions of some durables are mainly replacements in a rich region while they are mostly first-time adoptions in a poor region. Our finding suggests that the subsidy policy would be more effective in poor regions. An additional reason for this effectiveness could be that poorer households are more sensitive to the price change due to the subsidy.

Though our study is on durable adoptions, the interaction effect between education and local spillovers, especially social learning, with respect to new technology adoption would be a promising direction for empirical research. 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.[14] It is likely that schooling may augment the social learning, thus accelerating the catching-up process of a poor country.

Notes

[1] 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.

[2] See Manski (1993).

[3] Both effects are also detected in our study. 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. Zhang et al. (2002) find eduction plays an important role in facilitating the diffusion of high-yielding varieties of seeds in India. 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.

[4] It seems reasonable to make this extension. A new technology may be materialized as a new product, such as computer, ATM, software, and etc. Especially, a WM 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.

[5]Network externalities can be divided into two types, direct and indirect network externalities (Farrell and

Saloner, 1985; Katz and Shapiro, 1985). The former is due to that the rise of user size leads to higher utility for each individual user, such as telecommunication network. The later refers to the situation that the user scale helps reduce the average cost of providing complementary goods, such as CTV repair services. This cost reduction would increase the user's net benefit.

[6] They were color television set (CTV), WM, refrigerator, black-white television set (BWTV), fan, radio recorder, camcorder, VCD player, camera, microwave, rice-cooker, air conditioner, pager, bicycle, automobile, and motorcycle. Special attentions were paid to the first three durables.

[7] One may expect the adoption of CTV to be similar. It turns out the situation is more complicate with BWTV involved in (Rong, 2011).

[8] Owning more than one durable was minor. They are excluded from our examination since we only have the information on the year of their latest adoption. For this reason, 13 valid observations are deleted when we examine WM adoptions, and six are deleted for refrigerator.

[9] 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.

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

[11] The related estimation results are available upon request from the authors.

[12] Our tests closely follow Chen, Huffman and Rozelle (2011).

[13] 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.

[14] 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?"

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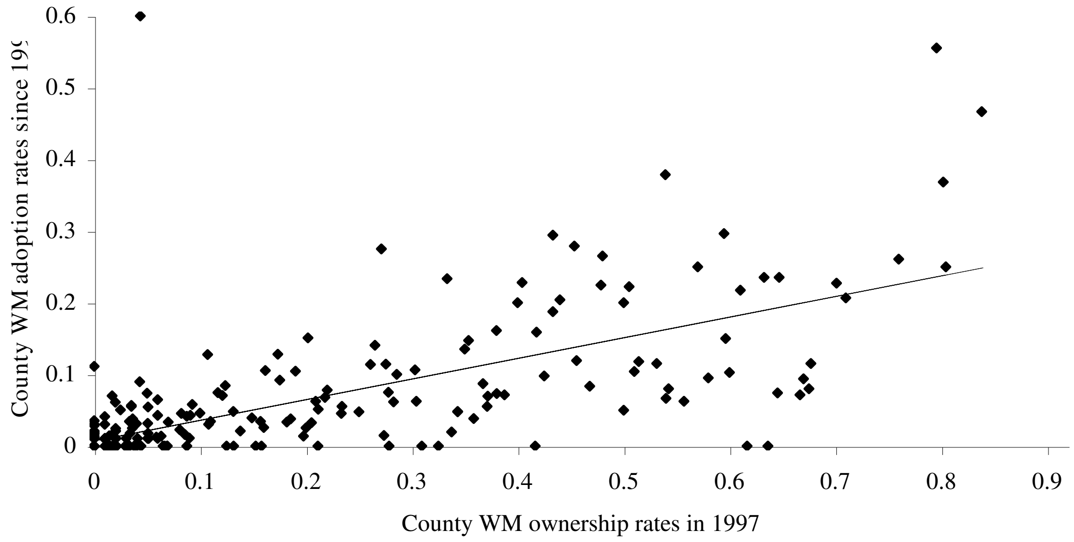

Figure 1. Washing machine adoption rates since 1998 at the county level.

Table 1

Summary statistics by owners and non-owners.

Variable	Washing Machine Non-owner	Washing Machine Adopter Since 1998	Washing Machine Adopter Before 1998	Refrigerator Non-owner	Refrigerator Adopter Since 1998	Refrigerator Adopter Before 1998
Village ownership rate in 1997	0.09	0.31	0.59	0.04	0.22	0.50
	(0.17)	(0.25)	(0.26)	(0.10)	(0.24)	(0.30)
Average net income (1,000 yuan)	2.02	2.77	2.98	2.08	3.51	3.87
	(1.42)	(1.86)	(2.03)	(1.42)	(2.39)	(2.35)
Average years of education	5.49	6.24	6.33	5.59	6.41	6.64
	(1.93)	(1.78)	(1.83)	(1.91)	(1.80)	(1.87)
Average age (years)	32.1	32.8	32.5	31.9	33.5	34.7
	(10.6)	(8.8)	(9.3)	(10.3)	(9.3)	(9.7)
Population	4.26	4.19	4.14	4.25	4.12	4.01
	(1.23)	(1.20)	(1.19)	(1.22)	(1.28)	(1.24)
Fraction male	0.52	0.54	0.52	0.52	0.54	0.53
	(0.22)	(0.21)	(0.21)	(0.22)	(0.22)	(0.22)
Education years of the head	8.16	8.59	8.80	8.26	8.56	8.77
	(2.52)	(2.26)	(2.21)	(2.48)	(2.31)	(2.30)
Fraction illiterate, the head	0.04	0.02	0.01	0.03	0.02	0.01
	(0.19)	(0.14)	(0.11)	(0.18)	(0.13)	(0.12)
Fraction elementary, the head	0.31	0.24	0.23	0.30	0.28	0.24
	(0.46)	(0.43)	(0.42)	(0.46)	(0.45)	(0.43)
Fraction junior high, the head	0.51	0.58	0.57	0.53	0.53	0.54
	(0.50)	(0.49)	(0.49)	(0.50)	(0.50)	(0.50)
Fraction senior high, the head	0.14	0.15	0.18	0.14	0.17	0.20
	(0.34)	(0.36)	(0.38)	(0.35)	(0.38)	(0.40)
Fraction associate, the head	0.00	0.01	0.01	0.00	0.00	0.01
	(0.06)	(0.08)	(0.10)	(0.07)	(0.06)	(0.09)
Electricity price (yuan/kWh)	0.79	0.69	0.63	0.77	0.66	0.60
	(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	0.06
Fraction in rural village	0.92	0.89	0.85	0.92	0.86	0.82
Fraction with stable electricity	0.92	0.96	0.96	0.92	0.94	0.98
Fraction with tap water	0.27	0.46	0.55			
Observations	9754	470	2486	11692	293	954

Note. Standard deviations are in parentheses.

Table 2

LP estimations of the likelihood of durable adoptions since 1998.

Variable	Washing Machine	Refrigerator
	(1)	(2)
$village\%_{t-1}$	0.149***	0.201***
	(0.030)	(0.044)
Average net income	0.014***	0.011***
	(0.002)	(0.002)
Average years of education	0.005***	0.002**
	(0.001)	(0.001)
Average age/100	-0.029	-0.010
	(0.021)	(0.014)
Population	0.009***	0.008***
	(0.002)	(0.002)
Fraction male	0.018*	0.011
	(0.011)	(0.008)
Town dummy	-0.001	0.003
	(0.020)	(0.018)
Rural village dummy	-0.006	-0.002
	(0.014)	(0.009)
Electricity stability	0.003	-0.006
	(0.007)	(0.005)
Electricity price	0.000	-0.003
	(0.015)	(0.007)
Having tap water	0.005	
	(0.008)	
Observations	10214	11982
Adjusted R^2	0.105	0.113

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

Table 3

LP estimations of adoption likelihood with more controls for unobservables.

Variable		(1)	(2)	(3)	(4)
Having other durables		Baseline	Y	N	Y
Other durable ownership rates			N	Y	Y
Washing Machine	$village\%_{t-1}$	0.149***	0.139***	0.135***	0.152***
		(0.030)	(0.030)	(0.032)	(0.033)
	Observations	10214	8825	9535	8825
	Adjusted R^2	0.105	0.127	0.107	0.130
Refrigerator	$village\%_{t-1}$	0.201***	0.184***	0.158***	0.171***
		(0.044)	(0.046)	(0.046)	(0.048)
	Observations	11982	10399	11171	10399
	Adjusted R^2	0.113	0.114	0.109	0.114

Note. *, **, ***: Coefficient different from zero at 10, 5, 1 percent significance levels, respectively. County dummies are included.

Table 4
IV estimations of adoption likelihood since 1998.

	Baseline	IV: Village means		
		IV 5 village means	IV Deleting population and fraction male	IV Deleting average age, population, and fraction mal
	(1)	(2)	(3)	(4)
village%$_{t-1}$	0.149***	0.256	0.321	0.321
Washing Machine	(0.030)	(0.187)	(0.204)	(0.204)
Observations	10214	10214	10214	10214
Endogeneity test				
Durbin (score) chi2		0.73 (p = 0.393)	1.62 (p = 0.203)	1.62 (p = 0.203)
Wu-Hausman F		0.71 (p = 0.398)	1.59 (p = 0.208)	1.59 (p = 0.208)
Robust F		0.34 (p = 0.558)	0.75 (p = 0.388)	0.74 (p = 0.388)
Overidentification test				
Sargan chi2		2.71 (p = 0.607)	0.70 (p = 0.703)	0.70 (p = 0.406)
Weak IV test				
Robust F		5.19	7.25	10.88
Stock-Yogo F		36.96	53.21	79.82
village%$_{t-1}$	0.201***	0.803**	0.947**	0.946**
Refrigerator	(0.044)	(0.386)	(0.419)	(0.419)
Observations	11982	11982	11982	11982
Endogeneity test				
Durbin (score) chi2		15.23 (p = 0.000)	21.33 (p = 0.000)	21.31 (p = 0.000)
Wu-Hausman F		14.96 (p = 0.000)	20.96 (p = 0.000)	20.95 (p = 0.000)
Robust F		2.89 (p = 0.090)	3.86 (p = 0.050)	3.86 (p = 0.050)
Overidentification test				
Sargan chi2		11.56 (p = 0.021)	0.64 (p = 0.726)	0.46 (p = 0.498)
Weak IV test				
Robust F		2.61	3.62	5.41
Stock-Yogo F		38.07	57.89	86.84

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

Table 5
The interaction effects of education level and local spillovers on durable adoptions.

Variable	Washing Machine			Refrigerator		
	(1)	(2)	(3)	(4)	(5)	(6)
$village\%_{t-1}$	0.026***			0.043***		
*Average years of education	(0.007)			(0.012)		
$village\%_{t-1}$		0.018***			0.020***	
*Education years of the head		(0.005)			(0.007)	
$village\%_{t-1}$			0.145***			0.319***
*Elementary dummy			(0.054)			(0.091)
$village\%_{t-1}$			0.174***			0.193**
*Junior high dummy			(0.056)			(0.075)
$village\%_{t-1}$			0.169**			0.247**
*Senior high dummy			(0.073)			(0.110)
$village\%_{t-1}$			0.899*			0.717*
*Associate dummy			(0.461)			(0.372)
Observations	10214	10214	10214	11982	11982	11982
Adjusted R^2	0.174	0.172	0.173	0.183	0.179	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.