SMART PHONES SUPPORT SMART LABOR

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Abstract:

Besides enabling communication, mobile phones and smartphones support information flows and financial transactions, especially in developing countries, where the coverage of landline networks is limited. Drawing upon new data from rural households in Southeast Asia, this paper shows that mobile phone or smartphone ownership supports local employment and commuting while it reduces incentives for migration of workers.

Keywords: smartphones; mobile phones; labor markets; labor mobility; economic development; Southeast Asia

JEL classifications: J61; O33; O53; R11

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1. Introduction

Mobile communication, money exchange[1] and Internet access have widely spread across the *developing world*. Several studies show that mobile phones can foster the spread of market information in the agriculture and fishery sector (JENSEN, 2007; AKER, 2010; TADESSE & BAHIIGWA, 2014). *Smartphones*[2] extend the scope of Internet-based market information access and market-based transactions. Forecasts reckon that by 2020 eighty percent of the world's adult population will own a smartphone, whereas today already half of the adult population owns one (THE ECONOMIST, 2015). The following paper argues that such intense technical progress creates impacts on *labor markets*.

Whereas the literature on mobile phones has focused on commodity markets (agriculture and fishery sector, see above), it has rarely addressed labor markets. Using experimental data from Peru, DAMMERT ET AL. (2013), as a notable exception, find with that job market information sent to job seekers via SMS (Short Message Service) raises job gain expectations, which may improve the future job status. The following paper investigates the hypothesis that mobile ICTs (information and communication technologies), in particular mobile phones and smartphones, enhance the participation of villagers who are usually engaged in subsistence farming, in off-farm labor markets. Mobile ICTs can ease labor market participation and mobility in three ways. First, information about local, adjacent or remote job vacancies can be accessed (NGA & MA, 2008; DAMMERT ET AL., 2013). Second, financial transactions, for example wage payments, can be executed (AKER & MBITI, 2010). Third, mobile ICTs allow absent workers to communicate with their families and peer groups at home (URETA, 2008).

This paper utilizes three spatially distinct types of off-farm employment as dependent variables: local employment within the village, commuting and labor migration to locations outside the village. The paper contributes to the literature by distinguishing between regular mobile phones and smartphones as explanatory variables. Both explanatory variables are endogenously determined. Whereas the literature has placed emphasis on Africa, the following paper draws upon

[1] "M-Pesa" in Africa and "Wing" in Asia.

[2] A Smartphone has a touch-screen, provides Internet access and enables the installation of software applications ("apps").

novel survey data from rural households in *Southeast Asia* (Thailand, Vietnam, Laos and Cambodia).

2. Model

We test the hypothesis that mobile ICTs support labor market participation and mobility. We test this hypothesis for mobile phones as well as for smartphones.

For this purpose, we set up an econometric model consisting of two equations. The first equation describes mobile ICT ownership, P_h, by household, h, in a given year. Mobile ICT ownership represents the treatment. It is indicated by $P_h = 1$ and implies that a household owns at least one mobile phone (including all kinds of mobile phones and smartphones) or alternatively at least one smartphone (a subtype of mobile phones, Supplement A). No ICT ownership is symbolized by $P_h = 0$. We explain mobile ICT ownership based on the following cross-sectional probit selection (treatment) model:

(1) $$P_h = \begin{cases} 1 \ \text{ if } \ \alpha_0 + \alpha_1 \cdot P_{dh} + \alpha_2 \cdot A_h + \alpha_3 \cdot E_h + \alpha_4 \cdot I_h + \alpha_5 \cdot T_h + \varepsilon_{1h} > 0 \\ 0 \ \text{ otherwise} \end{cases}$$

P_{dh} represents the average mobile ICT ownership within the same administrative district ($0 \leq P_{dh} \leq 1$); it captures rural technology diffusion via spatial correlation. A_h symbolizes the average household age: younger people tend to a have stronger affinity to modern technologies. E_h signifies education and is measured as the highest number of years that any household member spent for education; it is expected to raise technological understanding and hence the probability of ICT ownership. We expect households' annual income per capita, I_h, to raise the probability of ICT ownership as well. Likewise, wealth is represented by the value of households' tangible assets, T_h, which we expect to enhance ICT ownership. All α-parameters are to be estimated. ε_{1h} is the error term of the first equation.

The second equation explains the impact of mobile ICT ownership on the number of off-farm workers (laborers), labeled as L_h, of a specific type in household h. The three types comprise local employees working within the village, commuters with daily returns, and emigrants working outside the village without daily returns (Supplement B). The equation is characterized by the following linear, cross-sectional (outcome) model:

$$(2) \qquad L_h = \beta_0 + \beta_1 \cdot P_h + \beta_2 \cdot Q_h + \beta_3 \cdot S_h + \beta_4 \cdot E_h + \beta_5 \cdot M_h + \beta_6 \cdot C_h + \underline{\beta_7} \cdot \underline{X}_v + \sum_p \gamma_p + \varepsilon_{2h}$$

P_h and Q_h are two different mobile ICT variables. P_h is the endogenous mobile ICT variable explained by Equation (1). If P_h denotes endogenous *smartphone* ownership, then Q_h denotes exogenous *mobile phone* ownership, and vice versa. Household size, S_h, measures the number of people belonging to the household and captures the scale effect. As before, E_h signifies education which is deemed to be a major determinant of job opportunities. M_h denotes a binary variable that becomes 'one' if a household belongs to a local ethnic majority; it captures social privileges that may influence job opportunities. C_h signifies households' annual consumption value per capita, which reflects affluence. $\underline{X}_v$ symbolizes a column-vector of village-specific characteristics, v. It contains two geographic measures for the accessibility of a village: the travel time to the next town in the same province and the rank of the main road leading to the village, where 'one' indicates the best (two-lane made road) and 'five' the least quality (track/path). A longer travel time and unfavorable road conditions are expected to hinder labor mobility. Furthermore, the vector contains a binary variable which symbolizes the availability of Internet services via any technology in a village by 'one'. $\underline{\beta_7}$ defines a row-vector that contains $\underline{X}_v$'s coefficients. γ_p signifies p-, i.e. province-specific, effects in form of binary variables. All β-parameters are to be estimated. ε_{2h} is the error term of the second equation.

3. Data

We draw upon household data which were collected in the rural Southeast Asian Mekong region in the year 2013 (Supplement C). The data cover rural areas in Thailand and Vietnam (as analyzed by HARDEWEG ET AL., 2012, for previous years) as well as Laos and Cambodia as new research areas. The data cover more than 5000 households in approximately 500 villages. Villages were chosen with a three-stage stratified random sampling technique; overrepresentation of poor households in Vietnam and Laos is corrected with sampling weights.

The data contain households' number of mobile phones as well as the age and the value of the most recently bought mobile phone. We assume the lowest price for a smartphone fabricated in China including tariffs and taxes, equivalent to 2014-US[3]-$50, as the standard threshold price, above which a recently purchased mobile phone is treated as a smartphone. Accordingly, 92 percent of all households own a mobile phone, whereas 15 percent (distributed across all provinces and a wide range of income levels) own a smartphone.[4] Households' average annual per capita income amounts to 2005-PPP[5]-$2254.

4. Estimation

We jointly estimate Equations (1) and (2) as a *linear endogenous treatment regression (ETR)* (based on HECKMAN, 1978). We utilize the *maximum likelihood* (ML) criterion (MADDALA, 1983) letting ε_{1h} and ε_{1h} be correlated and bivariate-normally distributed (CAMERON & TRIVEDI, 2010: 193). A Wald-test mostly rejects the null hypothesis of statistical independence of the two equations. This implies that ETR is preferable over propensity score-based estimators which require independence (unconfoundedness). Furthermore, the criterion of independent and identically distributed individuals (stable unit treatment value) is violated due to the diffusion of mobile ICTs and information obtained from mobile ICTs (spatial correlation). Another Wald-test clearly rejects the null-hypothesis that all estimated parameter values (except the constant) are equal to zero. Correlations between regressors within one regression step are low (Supplement D), and collinearity across the two estimation steps is limited (PUHANI, 2000). Individual effects turn out to be largely insignificant in the first-step regression and are therefore left out. One of eight province-specific effects is left out in each second-step to avoid collinearity. We always use robust standard errors. We obtain the *average treatment effect (ATE)* of smartphone or mobile phone ownership with respect to the number of workers of a specific type, given by the estimated β-parameter values for P_h and Q_h.

[3] United States (of America).

[4] The correlation between mobile phones and smartphones is 0.14.

[5] Purchasing power parity.

5. Results

Table 1 about here.

Table 1 shows the results, in which mobile phone ownership is endogenous. It generates a statistically and economically significant positive effect on the number of local workers and commuters but a negative effect on emigrant workers. Smartphone ownership, here exogenous, has a significant and positive effect on commuters only. Besides, most estimates for the control variables have the expected signs. Substantial spatial correlation within districts indicates rural technology diffusion. Unfavorable conditions of the main road leading to the village hinder local employment, whereas a longer travel time to the next town in the province hinders commuting. Internet access within the home village has no significant effect.

Table 2 about here.

In Table 2 smartphones are treated as endogenous. Qualitatively, they create the same effect on workers as mobile phones in Table 1. Quantitatively, the magnitudes of the positive effects on local workers and commuters are higher, whereas the negative effect on emigrants is smaller than for mobile phones. Mobile phones, treated as exogenous in Table 2, has a significant and positive effect on local workers and a significant and negative effect on emigrants with smaller magnitudes than in Table 1. Most of the remaining results are similar to those in Table 1.

As a robustness check we use the average instead of the lower-bound price for a Chinese-brand device to define smartphones. The results corroborate those in Table 2 while creating larger magnitudes (Supplement E).

6. Conclusion

The results indicate that mobile ICTs support the efficiency of local rural labor markets within villages and their surroundings and hence reduce incentives for job-seeking emigration from villages. Better information about vacant jobs and possibly phone-based financial transactions seem to play a more important role than better communication capabilities for remote migrant workers. The positive labor market effect has a stronger magnitude for smartphones than for mobile phones, presumably due to the additional features that smartphones offer.

We conclude that development policy or foreign aid may improve local working perspectives for villagers in low-income countries by fostering the use of modern mobile ICT. One policy option is the passive support of infrastructure such as cell towers; another is the active support of ICT hardware, e.g. information about smartphones or interest-free credits to purchase them. Moreover, job information could be distributed via SMS (mobile phones) (cf. DAMMERT ET AL., 2013) or Internet platforms (smartphones).

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8. Supplement

Supplement A: Definition of the smartphone variable

The survey data for the year 2013 contain information about a household's, h, most recently obtained mobile phone, purchased during the years, $t \in \{2010, 2011, 2012, 2013\}$ and its purchase price, p_{ht} (i.e. the value according to the respondents). Households reside within one of the countries, $c \in$ {Thailand, Vietnam, Laos, Cambodia}. For each country and year, we calculate a threshold price, above which mobile phones are treated as smartphones:

$$\tilde{p}_{ct} = \bar{p} \cdot \epsilon_{ct} \cdot \delta_{ct} \cdot (1 + \tau_{ct}) \cdot (1 + \theta)^{2014-t} \tag{3}$$

We express $\tilde{p}_{ct}$ in 2005-PPP[6]-\$ in order to relate it to our survey data which are measured in the same unit. $\bar{p}$ denotes a given threshold price measured in 2014-US-\$. Most smartphones sold in Southeast Asia have been manufactured in China. Hence, we choose the *lowest* selling price for a Chinese-brand smartphone in 2014, 2014-US-\$50, according to GFK (2014) as the threshold price, $\bar{p}$, for the main regressions. The *average* price for a Chinese-brand smartphone in 2014 was 2014-US-\$159, which we use as an alternative threshold price in a robustness check (Supplement E). ϵ_{ct} symbolizes a PPP-based exchanged rate and δ_{ct} a country-specific CPI[7]-based deflator, which we calculate with CPI data published by the WORLD BANK (2015). τ_{ct} is an ad-valorem rate that captures local taxes and import tariffs. We use tax rates from the WORLD BANK (2015) and tariff rates from WTO (2015). θ represents the rate of technical progress in the fabrication of

[6] Purchasing power parity.
[7] Consumer price index.

smartphones, reflected by annual price reductions for smartphones. We follow DESILVER (2013) who suggests a rate of $\theta = 0.0835$.

We introduce an auxiliary variable that denotes a specific smartphone, S_{ht}', owned by household h in t, with a corresponding specific purchase price, p_{ht}'. We can now define that a household h, residing in country c, owns ‘at least one smartphone’ so that the endogenous binary variable P_h used in our regressions becomes $P_h = 1$ if $\sum_t S_{ht}' > 0$ where $S_{ht}' = 1$ if $p_{ht}' \geq \tilde{p}_{ct}$. Otherwise, the household owns ‘no smartphone’ so that $P_h = 0$. The same definition applies to the exogenous binary variable Q_h. The difference to P_h is that Q_h is not modeled endogenously. In the regressions, one of the variables, P_h or Q_h, refers to smartphones, the other one to mobile phones, so that either smartphones or mobile phones are modeled endogenously in each regression.

Supplement B: Definition of the labor variables

Whereas the usual occupation in rural Southeast Asia is subsistence farming, our analysis focuses on off-farm employment. It uses the number of workers as the dependent variable of the second-step (outcome) equation. Off-farm employment is defined as any employment, in which a person works for another person or entity based on a mutual contract. Off-farm employment usually leads to monetary or non-monetary income while the employed person does not carry the income risk related to the activity he or she is employed for. Under this definition, off-farm employment includes all kinds of jobs such as housemaid, driver, agricultural worker on another person’s farm, construction worker, mechanic in a workshop, sales assistant, and so forth. It does not include labor on a farm owned by the same household, fishing, hunting or logging activities at the account of the household nor does it include labor in business owned by the household.

We spatially distinguish between three types of off-farm employment: local employment takes place in a worker’s home village. Employment associated with commuting takes place in a location outside the home village, while the employee returns to the village daily. Employment associated with labor emigration is defined as working outside the village without returning daily. For each type, we utilize the number of workers as the unit of measurement.

Supplement C: Descriptive summary statistics

Our novel data were collected in household surveys in the rural Southeast Asian Mekong region at the beginning of the year 2013. They cover eight provinces in four countries: Buriram, Nakhon Phanom and Ubon Ratchathani in Thailand; Dak Lak, Ha Tinh and Thua Thien Hue in Vietnam; Savannakhet in Laos; and Stung Treng in Cambodia. Figure Supplement C illustrates the survey area. Table Supplement C describes the data.

Figure Supplement C about here.

Table Supplement C about here.

Supplement D: Correlations between regressors

The following matrix depicts the correlations between the regressors of both regression steps.

Table Supplement D about here.

Supplement E: Alternative definition of smartphones

In this robustness check, we consider an alternative definition of smartphones. Instead of the lowest selling price for a Chinese-brand smartphone in 2014, 2014-US-$50, we assume the average price for a Chinese-brand device in 2014 to be 2014-US-$159. This reduces the share of households with at least one smartphone in all households from twelve to 1.5 percent. The following table shows the results with endogenously modeled smartphones following this alternative definition.

Table Supplement E about here.

Compared to Table 2, the magnitudes of the positive and significant effect of smartphones on the number of local workers and commuters and the negative and significant effect on the number of emigrant workers are larger. Spatial correlation, represented by smartphone ownership within the district, is much more pronounced than in Table 2.

Table 1: Labor market effects of mobile phone ownership (binary) by rural Southeast Asian households.

Column number	1		2		3	
Estimation method	ETR (ML)		ETR (ML)		ETR (ML)	
	Outcome linear	Treatment probit	Outcome linear	Treatment probit	Outcome linear	Treatment probit
Dependent variable	Local workers	MPhone	Commuters	MPhone	Migrants	MPhone
Mobile phone	0.29*****		0.18*****		-1.34*****	
	(1.7e-06)		(0.00028)		(0)	
Smartphone	0.0050		0.085**		-0.069	
	(0.88)		(0.011)		(0.12)	
Household size	0.020****		0.036*****		0.19*****	
	(0.0035)		(2.9e-07)		(0)	
Education	0.00094		0.011*****		0.044*****	
	(0.72)		(8.1e-06)		(0)	
Ethnic majority	-0.100****		0.0047		0.13*****	
	(0.0025)		(0.84)		(0.00071)	
Consumption per capita	-0.000029*****		-7.2e-07		0.000041*****	
	(3.2e-06)		(0.94)		(0.00062)	
Time to province town	-0.00031		-0.0018*****		-7.2e-06	
	(0.25)		(0)		(0.98)	
Road rank	-0.044***		-0.014		0.022	
	(0.0054)		(0.22)		(0.21)	
Internet access	-0.030		0.0066		-0.035	
	(0.30)		(0.77)		(0.29)	
Mobile phone district		4.62*****		4.59*****		3.06*****
		(0)		(0)		(0)
Average age		-0.022*****		-0.022*****		-0.016*****
		(0)		(0)		(0)
Education		0.056*****		0.054*****		0.054*****
		(1.6e-08)		(3.0e-08)		(0)
Income per capita		0.000030		0.000032		7.9e-06
		(0.15)		(0.14)		(0.40)
Tangible assets		0.000065**		0.000066**		0.000061***
		(0.022)		(0.025)		(0.0097)
Constant	0.65*****	-2.67*****	-0.072	-2.64*****	0.0047	-1.55*****
	(0)	(0)	(0.27)	(0)	(0.97)	(9.7e-09)
Province dummies	yes	no	yes	no	yes	no
Number of observations	5,073	5,073	5,073	5,073	5,073	5,073

Robust *p*-values in parentheses, significance levels: ***** p<0.001, **** p < 0.005, *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 2: Labor market effects of smartphone ownership (binary) by rural Southeast Asian households.

Column number	1		2		3	
Estimation method	ETR (ML)		ETR (ML)		ETR (ML)	
	Outcome linear	Treatment probit	Outcome linear	Treatment probit	Outcome linear	Treatment probit
Dependent variable	Local workers	SPhone	Commuters	SPhone	Migrants	SPhone
Smartphone	1.16*****		0.80*****		-0.24****	
	(0)		(0)		(0.0015)	
Mobile Phone	0.091***		-0.0072		-0.14***	
	(0.0058)		(0.79)		(0.0059)	
Household size	0.010*		0.032*****		0.19*****	
	(0.097)		(1.4e-06)		(0)	
Education	-0.0057**		0.0075****		0.030*****	
	(0.044)		(0.0050)		(0)	
Ethnic majority	-0.076**		0.0056		0.089**	
	(0.011)		(0.81)		(0.023)	
Consumption per capita	-0.000037*****		-7.9e-06		0.000030***	
	(3.1e-08)		(0.42)		(0.0055)	
Time to province town	-0.000026		-0.0016*****		0.00022	
	(0.92)		(0)		(0.47)	
Road rank	-0.034**		-0.010		0.034*	
	(0.022)		(0.36)		(0.071)	
Internet access	-0.024		0.0019		-0.035	
	(0.35)		(0.93)		(0.31)	
Smartphone district		2.93*****		3.62*****		4.18*****
		(0)		(0)		(0)
Average age		-0.0064*****		-0.0098*****		-0.013*****
		(0.00058)		(0.00017)		(3.0e-07)
Education		0.028*****		0.025*****		0.031*****
		(1.9e-09)		(0.000041)		(5.1e-08)
Income per capita		0.000021*****		0.000029*****		0.000023*****
		(0.000010)		(0.000031)		(0.00091)
Tangible assets		3.1e-06**		4.8e-06**		8.9e-06*****
		(0.012)		(0.015)		(0.00049)
Constant	0.75*****	-1.55*****	0.080	-1.61*****	-1.00*****	-1.72*****
	(0)	(0)	(0.16)	(0)	(0)	(0)
Province dummies	yes	no	yes	no	yes	no
Number of observations	5,073	5,073	5,073	5,073	5,073	5,073

Robust *p*-values in parentheses, significance levels: ***** p<0.001, **** p < 0.005, *** p < 0.01, ** p < 0.05, * p < 0.1.

Figure Supplement C: Survey area.

Table Supplement C: Descriptive statistics.

Variable	Unit	Level	Mean	Std dev	Min	Max
Sample size	# observations	household	5073.00			
Local workers	# people	household	0.39	0.77	0.00	7.00
Commuters	# people	household	0.26	0.62	0.00	7.00
Migrants	# people	household	0.70	1.02	0.00	8.00
Average age	# years	household	35.83	11.50	10.00	90.00
Education	# years	household	10.00	4.49	0.00	35.00
Household size	# people	household	4.97	2.04	1.00	23.00
Income per capita	2005-PPP-$ / (# people)	household	2254.17	3303.85	°-4468.02	47480.40
Consumption per capita	2005-PPP-$ / (# people)	household	1952.82	1701.85	59.36	30667.90
Tangible assets	2005-PPP-$	household	6347.21	12739.97	0.00	276131.00
Ethnic majority	binary	household	0.82	0.38	0.00	1.00
Mobile phone	binary	household	0.92	0.28	0.00	1.00
Smartphone	binary	household	0.15	0.35	0.00	1.00
Internet access	binary	village	0.69	0.46	0.00	1.00
Time to province town	minutes	village	65.95	45.78	1.00	490.00
Road rank	1 ≡ best … 5 ≡ worst	village	1.71	0.98	1.00	5.00

° Negative income values occur due to depreciation or negative profits.

Table Supplement D: Correlations across regressors.

Variable	Size	Educ	Majority	Cons	Road	Town	Internet	SPhone	MPhone	Age	Income	Assets
Household size	1.00											
Education	0.14	1.00										
Ethnic majority	-0.09	0.21	1.00									
Consum per capita	-0.20	0.27	0.16	1.00								
Road rank	0.12	-0.29	-0.24	-0.20	1.00							
Time province town	0.09	-0.25	-0.30	-0.15	0.31	1.00						
Internet access	-0.10	0.26	0.15	0.19	-0.32	-0.32	1.00					
Smartphone	0.05	0.16	0.07	0.17	-0.09	-0.05	0.07	1.00				
Mobile phone	0.09	0.33	0.18	0.19	-0.23	-0.23	0.18	0.14	1.00			
Average age	-0.42	0.05	0.12	0.16	-0.28	-0.18	0.18	-0.01	-0.04	1.00		
Income per capita	-0.12	0.22	0.13	0.43	-0.15	-0.11	0.12	0.11	0.12	0.10	1.00	
Tangible assets	0.08	0.19	0.09	0.33	-0.14	-0.04	0.06	0.17	0.13	-0.01	0.21	1.00

Table Supplement E: Labor market effects of smartphone ownership assuming a higher smartphone price.

Column number	1		2		3	
Estimation method	ETR (ML)		ETR (ML)		ETR (ML)	
	Outcome linear	Treatment probit	Outcome linear	Treatment probit	Outcome linear	Treatment probit
Dependent variable	Local workers	SPhone	Commuters	SPhone	Migrants	SPhone
Smartphone	1.37*****		1.04*****		-0.66*****	
	(0)		(0)		(1.4e-07)	
Mobile Phone	0.10****		0.0090		-0.15****	
	(0.0042)		(0.74)		(0.0032)	
Household size	0.022*****		0.037*****		0.19*****	
	(0.00064)		(5.2e-08)		(0)	
Education	0.000010		0.011*****		0.030*****	
	(1.00)		(5.1e-06)		(0)	
Ethnic majority	-0.092****		0.015		0.085**	
	(0.0033)		(0.50)		(0.028)	
Consumption per capita	-0.000035*****		-3.7e-06		0.000031****	
	(7.8e-08)		(0.70)		(0.0047)	
Time to province town	-0.00019		-0.0017*****		0.00019	
	(0.48)		(0)		(0.53)	
Road rank	-0.048****		-0.014		0.034*	
	(0.0016)		(0.19)		(0.070)	
Internet access	-0.038		0.0048		-0.035	
	(0.18)		(0.82)		(0.31)	
Smartphone district		9.16*****		13.8*****		15.7*****
		(7.6e-09)		(4.7e-06)		(0)
Average age		-0.0041		-0.0057		-0.012**
		(0.30)		(0.27)		(0.041)
Education		0.028*****		0.029**		0.041*****
		(0.00021)		(0.022)		(0.00061)
Income per capita		0.000021*****		0.000034*****		0.000036*****
		(0.00027)		(0.00063)		(0.00012)
Tangible assets		3.7e-06****		6.5e-06**		0.000011*****
		(0.0010)		(0.022)		(0.00021)
Constant	0.80*****	-2.17*****	0.065	-2.65*****	-0.99*****	-2.87*****
	(0)	(0)	(0.26)	(0)	(0)	(0)
Province dummies	yes	no	yes	no	yes	no
Number of observations	5,073	5,073	5,073	5,073	5,073	5,073

Robust *p*-values in parentheses, significance levels: ***** p <0.001, **** p < 0.005, *** p < 0.01, ** p < 0.05, * p < 0.1.