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Can Two Consecutive Generations' Data Predict Long-term Intergenerational Transition? Evidence from China with three generations

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Abstract:
Most of the studies on long-term intergenerational human capital transition are restricted to two consecutive generations based on the Becker-Tomes model, and assume that the transition will be wiped out during the third generation. However, in developing countries such as China, ancestors play a key role in the family decision-making process. Thus, this research uses a data set of China rural households, which includes three generations of data, to analyze the long-term intergenerational transition. The results provide empirical evidence that separate generations have had an independent and significant influence on the offspring's human capital outcome. Precisely, the grandparent generation influences the child generation independently rather than influencing the child generation through the parent generation. Therefore, the influence of generations on educational achievements has been overestimated by the data that only encompass two consecutive generations.

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1 Introduction

Disparity of intergenerational human capital transition exists widely in education, income, and social status. In China, there is a social norm that the level of education changes people's fortune, which drives all society to pursue high educational achievements. Thus, this research focuses on the education transition between generations. The scope of the past research on long-term intergenerational human capital transition has been restricted to two consecutive generations: the parents and their children. The most cited method on measuring long-term intergenerational human capital transition is the Becker-Tomes model. This model assumes that the achievement of the child generation is influenced by the parent generation, and the grandparents influence the child generation through influencing the parent generation. If the prediction of the Becker-Tomes model were to be considerate perfect, the separate generation would have no influence on the human capital, in which the grandparent generation shall have no direct influence on the child generation.

There is a branch of overseas studies that discussed the long-term intergenerational human capital transition and relied on using data from just two consecutive generations (Golley, 2013; Labar, 2011; Congbin, 2008; Borjas, 1992; Cork, 2013; Chetty, 2014). However, a research conducted by Clark (2012) pointed out that the validity of two consecutive generations' analysis relies heavily on the validity of that assumed model. In addition, Stuhler (2013) shows that the extrapolation error — the difference between the extrapolated long-run persistence and true long-run persistence — cannot be ignored when only being based on data from two consecutive generations. Mikael (2016) argued that the Becker-Tomes model cannot easily be recovered from data only covering two generations, because it requires that the transition be an AR(1), either with a serially correlated endowment term that is uncorrelated with parents' outcome, or with a serially uncorrelated endowment term that might be correlated with parents' outcome. Therefore, the predictions based on two generations can be misleading.

China is known as a country that values family, and the family structure has thus played a key role in Chinese society. Considering the role of grandparents in the family, multiple channels may exist for them to influence the child generation and transform human capital independent of the parent generation. First, especially when their spouse dies, a grandparent may influence children directly by living with them. Second, a grandparent may give financial support through presents to the grandchildren directly if their grandchildren are admitted to a university, and for festival celebrations. Last, grandparents may influence their grandchildren directly by making decisions for them. Within the Chinese traditional family structure, there are several studies in the humanity field that discuss the grandparents' impact on children. One study done by Shi (1993) concluded that the grandparents play a significant role in raising the children when the parents are away for work. Chen (2000) examined how the physical conditions and well-being of the elderly in families are influenced by children, and the results showed that retired elderly parents gain personal satisfaction and self-esteem from taking care of their grandchildren. Therefore, the grandparents play a significant role in Chinese typical traditional families, and may have a strong independent influence on the young generation through several channels and for several reasons. Nevertheless, research on long-term intergenerational human capital transition is still mainly based on the data of two consecutive generations.

Since the Becker-Tomes model may be biased, it is necessary to analyze whether the long-term intergenerational human capital transition can be estimated with more than two consecutive generations' data. This research uses a data set of China rural households, which includes three generations for each household, to analyze the long-term intergenerational transition. We use the term "grandparents" for the first generation, "parents" for the second generation, and "children" for the third generation throughout this paper. The main purpose of this research is to measure to what extent can the data of two consecutive generations analyze the long-term intergenerational human capital transition. We began with a measurement of whether the grandparent generation directly influences the child generation's educational outcome, and compared the difference between the predicted transition and the real transition measured by two and three generations' data, respectably. The results confirmed that human capital transition has been overestimated by the data of only two consecutive generations.

In addition, we estimated another two models to prove. First, we used the educational outcome from the grandparent generation as the instrument for the outcome of the parent generation in the model suggested by Clark (2012). The results concluded that the AR(1) model failed to predict the long-term intergenerational transition due to the generation-specific deviations from the long-term social position of families. Second, we ran an AR(2) model that included both the parent and grandparent generation's educational achievement. The results suggested that the grandparent generation has a significant independent influence on the child generation's educational achievement.

Last, we explored whether the gender differences influence the intergenerational educational transition. The findings indicated that gender differences influence the outcome of the transition from the elders to their offspring.

This paper is organized as follows. Section 2 gives a short introduction of the international and China literature review for this research. A brief description of the data set is provided in

Section 3, and the empirical methodology and results are shown in Section 4. Section 5 discusses the gender differences between education mobility. The last section summaries the conclusion of this research and discusses the implications of the findings.

2 Literature review

The estimation of transition from parents to children is widely used in predicting the long-term intergenerational human capital transition. A research conducted by Chetty (2014) used population data of The United States to predict the intergenerational income transition through the parent to child generation. Their research concluded that intergenerational transition varies across the national income distribution and different regions. They suggested that the reason for spatial variation may be caused by factors of residential segregation, income inequality, school quality, social capital, and family structure. Solon (2002) discussed how the gender differences influence the income transition from the parent to child generation, and concluded that intergenerational income transition is consistently weaker for daughters than for sons.

Clark's (2013) research discussed what is the true rate of social mobility in Sweden with a sure name analysis. In this research, he introduced a latent variable of "luck of family social status" for each generation t, which can be interpreted as,

$$x_{t+1} = ax_t + e_t, (1)$$

$$y_t = x_t + \mu_t, (2)$$

$$y_{t+1} = by_t + v_t, (3)$$

where x is the latent variable, y is the outcome of social status, e, μ, and v are the error terms. In this situation, it could be possible that a is not equal to b, for,

$$E(\hat{b}) = a\frac{1}{1+(\frac{\sigma_u^2}{\sigma_x^2})}, (4)$$

Thus, it is clear that the result from two AR(1) model's prediction will be different than the prediction from the data of two separate generations apart. This comparison is provided in Section 4, and the results showed that the prediction is almost 10 times different between these two methods.

The studies in China that followed up with international research only used two consecutive generations of data to predict the intergenerational human capital transition. Qin (2016) used the 1989–2009 China Health and Nutrition Survey (CHNS) data to analyze the impact of the intergenerational transmission of human capital on the income mobility in China from the parent to child generations. Fan (2015) conducted a research using the 2010 Chinese Family Panel Studies (CFPS) to investigate the temporal patterns of cross-sectional inequality and intergenerational mobility during the economic reform era in China. Magnani (2015) analyzed China social mobility from the data of the 1990 and 2000 Chinese Population Censuses, and conclude that the intergenerational transition from the parent to child generations becomes increasingly stronger in China urban areas. Considering that the obtained predicted transition with two consecutive generations' data can be biased, this paper explores whether the long-term intergenerational human capital transition can be consistently predicted by the data of only two consecutive generations in China.

3 Data description

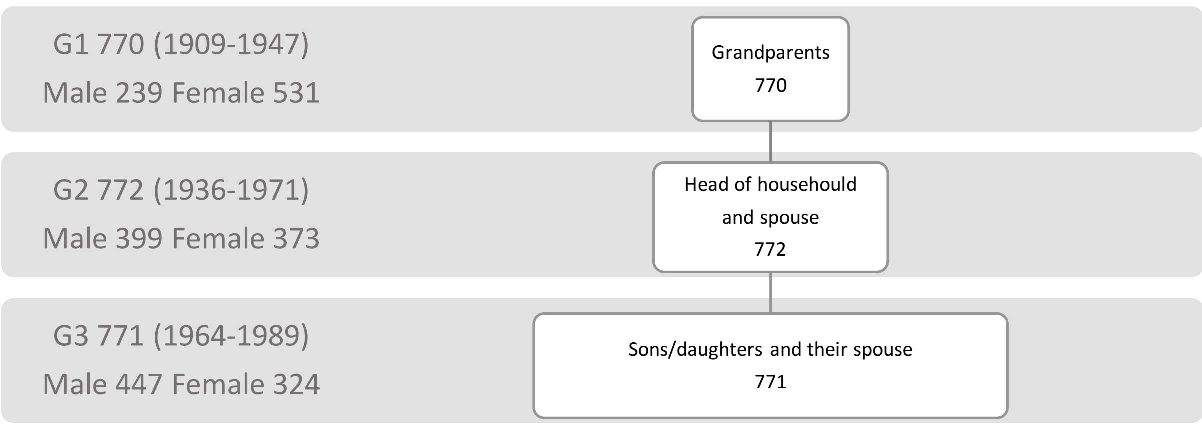
This research uses the household survey data called the Longitudinal Survey on Rural Urban Migration in China (RUMiC) from the Institute for the Study of Labor (IZA). The previous studies that used this data set focus on three different aspects of migration. The first one is regarding the relationship between remittance and migration. The second one is on the wage gap (Klaus et al. 2016; Rachel et al. 2015; Björn et al. 2014; Hartmut and Yuhao 2013; Klaus et al. 2014; Zhong et al. 2014). The last one concentrated on the well-being of migrants (Wei Huang 2015; Xin Meng and Chikako Yamauchi 2015) or education attendance of migrants' children (Massimiliano Tani 2016).

The RUMiC data set consists of three parts: The Urban Household Survey, Rural Household Survey (RHS) and Migrant Household Survey. The survey was initiated by a group of researchers at the Australian National University, the University of Queensland and the Beijing Normal University under a support of the IZA, which provides the Scientific Use Files. The financial support for RUMiC was obtained from the Australian Research Council, the Australian Agency for International Development (AusAID), the Ford Foundation, the IZA and the Chinese Foundation of Social Sciences. The RUMiC dataset is based on a face-to-face interview, and the interviews were conducted in 2008. This paper used the RHS dataset of 2008. The sampled households were selected randomly from nine provinces in China, namely Sichuan, Chongqing, Anhui, Hubei, Henan, Guangdong, Zhejiang, Jiangsu and Shanghai. This RHS dataset contains the information of the highest education accomplished for each household, which allows us to analyze the education transition within the household. The reason for using RHS only rather than combining it with the Urban Household Survey is that during the Chinese Culture Revolution, the parents of urban families had been sent to rural areas and may have had an influence on the analysis of education transition. Thus, we restricted our data to rural household data to analyze the education outcome correlation between the generations in the long term.

For all generations, we restricted the samples of households that have information for all three generations. The educational level was measured as years of schooling, which we calculated by the average years required for the highest educational degree accomplished. For the third generation, we discarded samples with ages younger than 20 in order to assure that our samples have the possibility to accomplish the compulsory education (in China the compulsory education consist of 6 years of primary education and 3 years of secondary education, which is generally completed at age 15 or 16). With these conditions, we were left with 772 useful samples of households usable for our estimation.

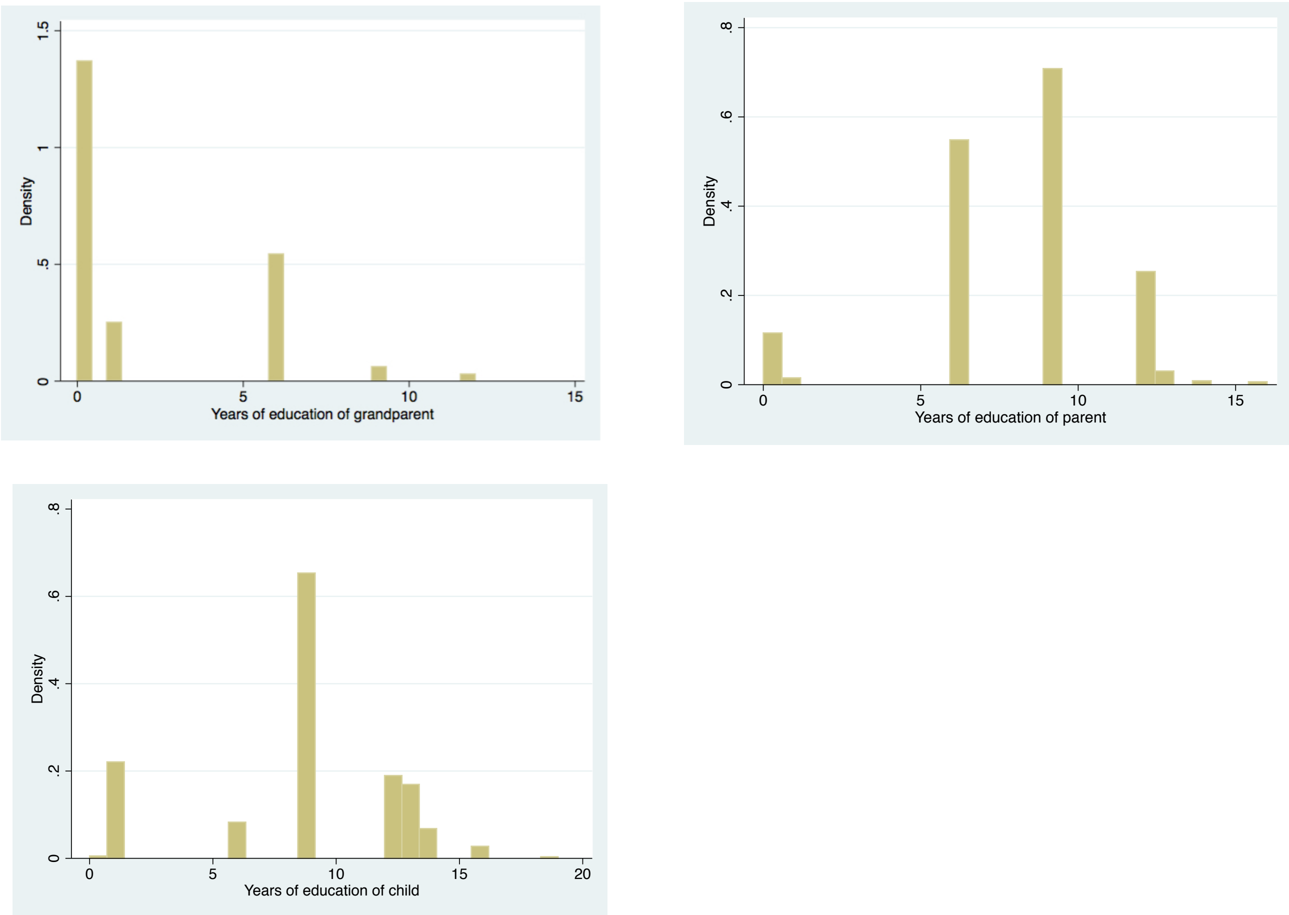
The intergenerational human capital transition is shown in Figure 1, and the educational achievement is presented in Figure 2. Table 1 gives the descriptive statistics for all the variables in the empirical analysis. Since the numbers of observations is almost the same across generations as shown in Figure 1, we are allowed to conduct the intergenerational transition analysis. From Figure 2, we find that the educational achievement is very low for each generation in China's rural areas. However, the years of education still shows slow growth through each generation from the grandparent to child generation.

Figure 1. The generation transition through three generations



Source: RHS 2008

Figure 2. Educational achievement for each generation



Source: RHS 2008

Table 1. Descriptive statistics

	Grandparent		Parent		Child	
	Male	Female	Male	Female	Male	Female
Years of schooling						
Mean	3.196653	1.401501	8.822055	6.935657	8.910515	8.707692
Std. Dev.	3.354263	2.657122	2.644975	3.331366	4.188501	3.82133
Min Max	[0, 12]	[0, 12]	[0, 16]	[0, 16]	[0, 19]	[0, 16]
Observations	239	533	399	373	447	325
Age						
Mean	80.2887	80.69868	52.26065	50.32976	26.03132	24.82716
Std. Dev.	7.138215	7.053139	6.548024	6.434626	5.193468	4.772963
Min Max	[62, 97]	[62, 100]	[38, 73]	[37, 68]	[20, 45]	[20, 42]
Observations	239	531	399	373	447	324

Source: RHS 2008

4 Methodology

As addressed before, the most cited model of intergenerational human capital transition is the Becker-Tomes model. The Becker-Tomes model measures mobility between the two generations using the framework of the first-order autoregressive process (AR(1)) of the time-series regression. The Becker-Tomes' two generation model is specified as:

$$y_t = \emptyset y_{t-1} + \tau e_t + u_t, \text{(5)}$$

$$e_t = \lambda e_{t-1} + v_t, \text{(6)}$$

where, y is the outcome such as educational achievement, e represents endowment, u and v are the error terms, t indicates the child generation, $t-1$ indicates the parent generation, $\emptyset$ is the estimated level of influence from the parent generation, and τ is the estimated level of endowment for the child generation. This model is under the strong assumption that τ = 0 or $\lambda = 0$. Although the Becker-Tomes model has an analogy with the AR(1) process by regarding the generation as time dimension, two-generation data only allows them to include the variables of a pair of parents and their children, which existed at the time of the survey. Under this condition, the AR(1) model omitted the endowment variable or assumed that the endowment is uncorrelated with the parents' outcome, and simplified their model into a cross-section model that can be estimated by the ordinary least squares (OLS). In addition, this framework can be easily extended to the three generation case by replacing y_{t-1} with y_{t-2}, allowing us to measure the grandparents transition so long as three-generation data is available. Thus, the estimation models for the two-generation and three-generation models can be written as:

$$y_{t,i} = a + by_{t-j,i} + d'X_i + u_i \text{ , (7)}$$

where $j \geq 1$, y_t is the education of the child and y_{t-j} is the education of the parents when j = 1, and grandparents when j = 2, and i indicates the household i. x_i is a vector of controls including a cubic in age for generation t and generation $t-j$, and gender dummies for generation t and $t-j$, and u_i is the error term. When j = 2, this model allows us to measure the influence of the grandparent generation on the child generation. Thus, through this model, the influence of the grandparent generation can be compared with that of the parent generation.

The estimation of this model allows us to discuss our results both from the regression coefficient and the predicted correlation coefficients. If the measuring of Becker-Tomes model holds well, the actual intergenerational transition therefore should be the same with the predicted transition from the two consecutive generations' data.

Figure 3 presents the difference between the concepts of our model (the dynamic model) and Becker-Tomes'. Our model allows us to examine the direct impact of the grandparent generation on the outcome of the child generation, instead of examining the indirect impact on the child generation through a direct impact on the parent generation.

Figure 3. Intergenerational transition in China rural area

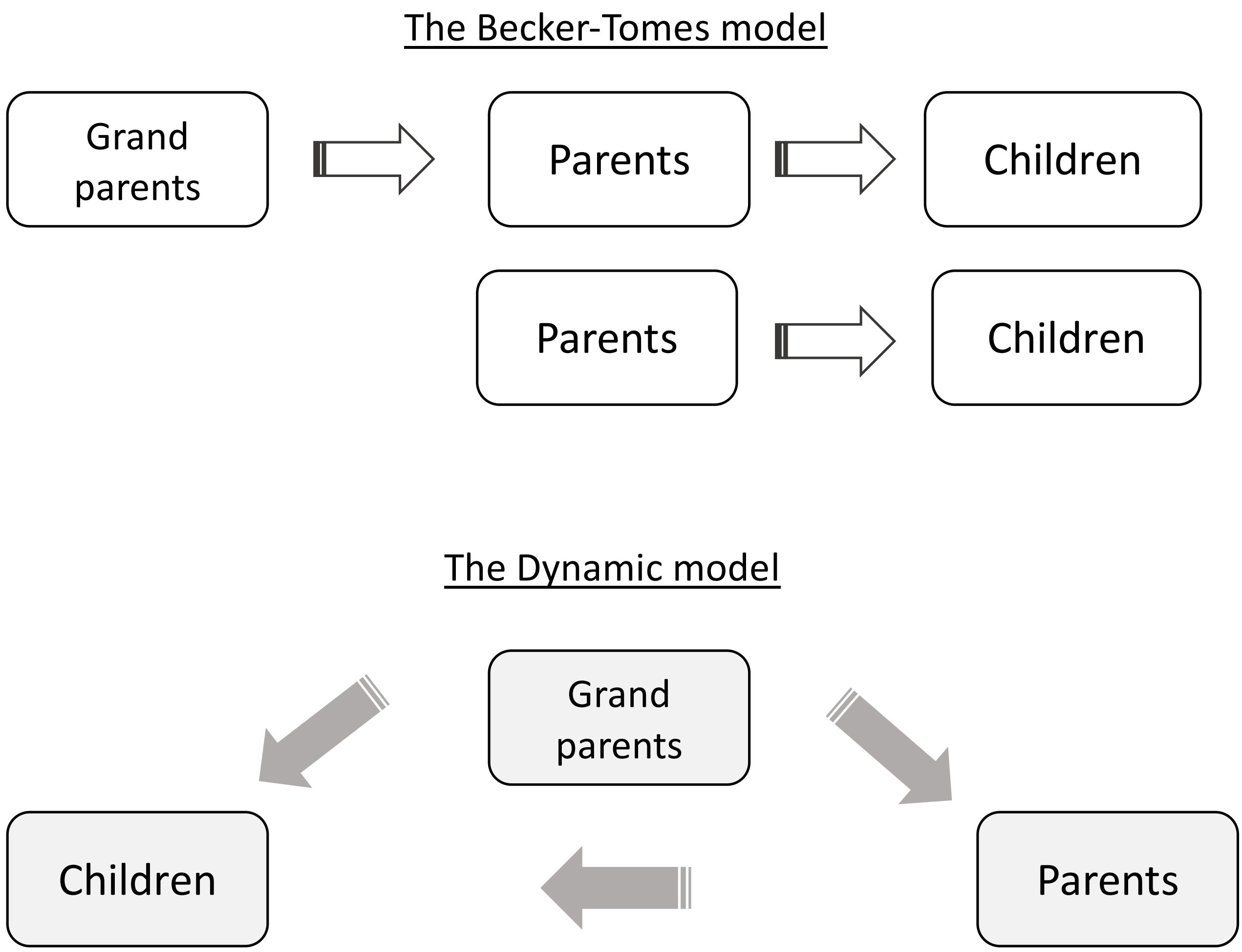


Table 2. Intergenerational human capital transition results from rural households

Variables	Years of schooling		
	Parent generation	Child generation	
Years of schooling of grandparents	0.110***	0.137**	
	(0.0395)	(0.0584)	
Years of schooling of parents			0.118**
			(0.0565)
Controls	yes	yes	yes
Constant	-208.0**	53.05	61.22
	(83.48)	(116.2)	(55.30)
Observations	770	769	771
R-squared	0.186	0.062	0.064
Prediction		0.01298	
		(0.11*0.118)	

Note: each column represents different regression results.
Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

The prediction from the Becker-Tomes model is shown in the Prediction line at the level of 0.01298. Table 2 presents the intergenerational human capital transition in two generations: (1) the education transition from the grandparent generation to the parent generation is 0.11, the the education transition from the grandparent generation to the child generation is 0.137, and the the education transition from the parent generation to the child generation is 0.118; (2) the education from the grandparent to child generation is statistically significant and not equal to 0; (3) the prediction from the Becker-Tomes model of the education transition from the grandparent to child generations is approximately 0.013(0.11*0.118), and almost 10 times smaller than the result from the regression, which is 0.137.

Therefore, we can conclude that the data of two consecutive generations has overestimated in the long-term intergenerational human capital transition. At the same time, we can reject the hypothesis that the data of two consecutive generations is adequate to analyze the long-term intergenerational human capital transition.

Next, in order to interpret why our results are different from the data of two consecutive generations, we conducted two other analyses after the main regression. One is the instrumental variable model suggested by Clark (2012), and the other is the AR(2) model where we extended the AR(1) model by including both the parents and grandparents generation in the regression.

The Clark model is an instrumental variable model using the grandparent generations' data as the instrumental variable to indicate the child generations' outcome, and is written as:

$$y_{t,i} = a + by_{t-1,i} + d'X_i + u_i, (8)$$
$$y_{t-1,i} = \pi' y_{t-2,i} + \theta' X_i + \varepsilon_i \ , (9)$$

where y_t is the outcome of the child and $y_{t-1}$is the outcome of the parents, y_{t-2} is the outcome of the grandparents, t represents the generation and i indicates the child. x_i is a vector of controls, u_i and ε_i are the error terms.

Table 3. Comparing the results between the basic model and the iv-model

VARIABLES	(1) Years schooling of child	(2) Years schooling of child
OLS		
Years schooling of parent	0.110***	0.118**
	(0.0395)	(0.0565)
	Observations=770	Observations=771
	R-squared=0.186	R-squared=0.064
IV		
Years schooling of parent	1.295**	1.295**
	(0.561)	(0.564)
Controls	yes	yes
Constant	161.4**	159.1**
	(79.09)	(78.48)
Robust score chi2(1)	7.47148**	7.45565**
Robust regression F(1,758)	7.37214**	7.35635**
Test of over-identifying restrictions Score chi2(1)		0.929403 (p = 0.3350)
	Observations=771	Observations=769
Instruments		
Years schooling of grandparents	Yes	Yes
Age of grandparents	No	Yes

Note: each column represents different regression results.
Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 3 presents the results both from the Becker-Tomes model (OLS/AR(1) model) and the instrumental variable model. The upper portion of column (1) shows the results from the grandparents' education attendance to the parents' education attendance, and the upper portion of column (2) shows the results of the parents' education attendance to the children's education attendance. The lower portion from Table 3 presents the results from the instrumental variable model on education attendance for the parent generation to the child generation. The lower portion for column (1) shows the results of using the variable of "years of schooling of grandparents" as the instrumental variable to "years of schooling of parents", and the lower portion for column (2) presents the results of using the variables of both "years of schooling of grandparents" and "age of grandparents" as the instruments. From Table 3, we can conclude that for the analysis regarding the relationship of education attendance between the parent generation and the child generation, the iv model is more superior than the AR(1) model, given that all of the falsification tests (endogenous test, weak iv test and over identifying test) support the iv strategy.

The AR(2) model is based on the AR(1) model, but includes a prior generation, and can be been written as:

$$y_{it} = a + b_1 y_{it-1} + b_2 y_{it-2} + d' x_i + \mu_i \text{ , (10)}$$

where y is the outcome, i is the individual household, t denotes the generation and u_{it} is the error term.

Table 4. Comparison between grandparents and parents

VARIABLES	Years schooling of child
Years schooling of parent	0.102**
	(0.0499)
Years schooling of grandparent	0.127***
	(0.0458)
Controls	yes
Constant	108.4
	-101.6
Observations	769
R-squared	0.073

Note: Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 4 gives the results of the AR(2) model. The results are clear in that the impact from the grandparent generation is significantly different from 0; in rural areas of China, "years schooling of grandparent" increased 0.127 years, and the education years to child generation rose by 1 year.

Therefore, we can conclude that only using two consecutive generations' data will over-estimate the long-term intergenerational human capital transition.

5 Extended research of gender differences

We discuss the influences of gender power on intergenerational human capital transition in this extended research section. Table 5 shows the transition from the parent generation to child generation. Table 6 presents the transition from the grandfathers, and Table 7 yields the transition from the grandmothers.

Table 5. Transition from parent generation to child generation

VARIABLES	Father to Son Years of education	Father to Daughter Years of education	Mother to Son Years of education	Mother to Daughter Years of education
Education of parent	0.197*	-0.240*	0.238**	0.0709
	-0.109	-0.13	-0.092	-0.0933
Controls	yes	yes	yes	yes
Constant	186.7**	28.53	-70.9	212.4**
	-79.89	-92.21	-113.5	-88.21
Observations	241	158	206	166
R-squared	0.094	0.08	0.111	0.069

Note: each column represents different regression results.
Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 6. Transition from grandfather

VARIABLES	Education of Father	Education of Mother	Education of Son	Education of Daughter
Education of grandfather	-0.108*	0.211**	-0.194*	0.0287
	(0.0577)	(0.103)	(0.0994)	(0.131)
Controls	yes	yes	yes	yes
Constant	-159.4	-278.4	85.72	-405.8
	(178.8)	(364.1)	(263.4)	(361.3)
Observations	146	93	133	106
R-squared	0.112	0.225	0.108	0.055

Note: each column represents different regression results.
Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table7. Transition from grandmother

VARIABLES	Education of Father	Education of Mother	Education of Son	Education of Daughter
Education of grandmother	0.148**	0.218***	0.357***	0.15
	-0.0657	-0.0685	-0.115	-0.0951
Controls	yes	yes	yes	yes
Constant	-302.7**	-136.0	288.3	-241.6
	(120.6)	(142.4)	(177.6)	(169.2)
Observations	252	279	312	218
R-squared	0.098	0.130	0.150	0.086

Note: each column represents different regression results.
Figures in parentheses are t statistics.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

From Tables 5, 6 and 7, we find that there are some differences in transition through elders by gender. First, females in general have a larger and positive influence on their offspring. It can be possible that most of the female elders are spending more time on taking care of their offspring. Second, male elders have a possible opposite influence on their offspring. This may be considered as male elders having a tendency to prefer one child among their offspring. Third, the females of the child generation tend to gain a small and non significant influence from their ancients compared with males.

6 Conclusion

This research provided evidence that the persistence of long-term intergenerational human capital transition in China's rural area is much stronger across three generations than two generations. In addition, this result has been confirmed by the Instrumental Variable model and the AR(2) model that include the information of three generations rather two generations.

One possible explanation for the result of the long-term intergenerational human capital transition in China is that the Chinese traditional family is a structure where the elderly are the decision makers who influence the whole family and other offspring.

Through the main empirical analysis and the further analysis models (the IV model and the AR(2) model), we can reject that the two consecutive generations data is adequate to analyze the long-term intergenerational human capital transition in China. Furthermore, our results line up with other overseas studies on long-term intergenerational transition (Lindahl 2015; Stuhler 2013). By dividing the sample by gender through the analysis of intergenerational human capital transition, we find that that there are some differences in transition through elders by gender.

The implication of this research is that only using two consecutive generations' data on long-term intergenerational human capital transition should be interpreted with caution, especially for those who are interested in developing countries and have similar traditional family cultures as China.

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Appendix

The representative of RUMiC data.

Compared with 2000's China's census data, the parent generation's data shows that the distribution of educational achievement is remarkably similar with each other. The following table provided the distribution of educational achievement for the parent generations from the RUMiC data as compared to the census data, obtained from the National Bureau of Statistics of the People's Republic of China, weighted to 10 million people.

Table of educational outcome from census and RUMiC

Education achievement	Census(10 million)	Parent generation
Elementary school	318	251
Junior middle school	244	324
Senior middle school	30	116
Specialized secondary school	8	14
Polytechnic college	3	4
Undergraduate	1	3
Postgraduate		
Wave of year	2000	2008