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# Labor migration, human capital agglomeration and regional development in China

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# 1. Introduction

Internal labor migration long has been viewed as central to efficient labor allocation. Aggregate labor productivity rises as workers move from less to more productive places (*e.g.*, Sjaastad, 1962; Gabriel et al., 1993). Further, research has demonstrated that workers relocate in response to differential returns to human capital (*e.g.*, Roy, 1951; Borjas et al., 1992; Dahl, 2002) and that such moves ease regional disparities in both productivity and skills as arise from exogenous shocks (Borjas, 2001; Whalley and Zhang, 2004). In the development literature, numerous studies (*e.g.*, Lewis, 1954; Ranis and Fei, 1961; Harris and Todaro, 1970) also have shown the importance of urban migration in reduction of rural–urban productivity gaps.

In this paper, we draw upon modern theories of economic growth and spatial equilibrium (Lucas, 1988; Romer, 1990; and Glaeser and Gottlieb, 2009), which emphasize increasing returns to human capital and agglomeration, to assess internal migration and regional economic development in China. In particular, we seek to provide new insights as regards disparate regional growth evidenced in China during the 1990s. Indeed, those disparities became more pronounced despite increased labor mobility and eased regulation of household location choice (see, for example, Fujita and Hu, 2001; Démurger et al., 2002; Candelaria et al., 2009; Villaverde et al., 2010). Our analysis highlights the influence

# ABSTRACT

We estimate a skill-based directional migration model to assess the effects of regional human capital agglomeration on labor migration in China. Upon accounting for regional differentials in skill-based compensation, cost-of-living, amenities, and the like, model estimates indicate the importance of destination human capital concentration to high-skill migrants. In marked contrast, low-skill migrants are found to have little incentive to co-locate with high-skill workers, likely reflecting institutional and other impediments to human capital investment among low-skill migrants. Research findings suggest the importance of human capital agglomeration benefits to disparate regional growth trajectories in China.

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of regional human capital agglomeration on disparate regional growth via migration choices among skill-based population strata.

Regional differences in human capital concentration can affect migratory incentives in various ways. First, such differences can affect the placespecific demand for skills. Giannetti (2003) and Berry and Glaeser (2005), for example, suggest that high concentrations of skilled people in cities generate more skilled jobs. In the presence skill complementarities, wage rates for skilled workers will be higher in areas of high human capital concentration. Second, concentration of human capital supports consumer amenities, such as cultural vibrancy, that attract high-skill people (e.g., Shapiro, 2006). Third, as suggested by Lucas (1988, 2004, 2009), Eaton and Eckstein (1997), Glaeser (1999) and Glaeser and Mare (2001), the concentration of proximate human capital results in spillover benefits to private investment in human capital and ideas, which in turn contribute to higher productivity growth for city migrants. The human capital spillover benefits are of particular importance to regional growth (e.g., Glaeser et al., 1995; Gennaioli et al., 2011). Accordingly, agglomeration of human capital may provide incentives for labor migration that reinforces spatial inequality in human capital concentration and economic development. In this paper we explore the hypothesis, as suggested by theory, that human capital spillover benefits in regions of human capital agglomeration resulted in divergent rates of migration across skill-based population strata in China. Such movement of population would then exacerbate disparities in regional growth among China's provinces.

Our empirical analysis employs a utility-maximizing directional migration model, which allows for competing migration incentives as well as heterogeneous migration costs and preferences in determination of

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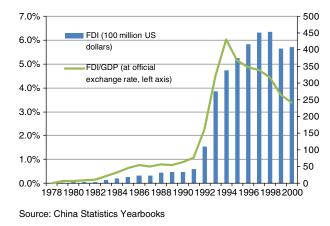


Fig. 1. Foreign Direct Investment in China (1978-2000).

mobility outcomes among population strata. Such models have been applied in the place-to-place migration literature, which offers evidence that regional differences in return to skills are important to the magnitude and to the skill composition of interregional migration flows (as in Roy, 1951).<sup>1</sup> That model has several distinct advantages relative to prior cross-sectional analyses of the effects of human capital agglomeration on regional economic growth (see, for example, Glaeser et al., 1995; Glaeser and Shapiro, 2003; Shapiro, 2006; Glaeser et al., 2011). First, directional migration analysis allows controls for destination fixed effects to account for unobserved locational heterogeneities.<sup>2</sup> Second, directional migration analysis accounts for spatial heterogeneity in destination labor supply arising from distance-sensitive migration costs. Third, application of the directional migration model focuses on gross population flows, which unlike net population growth, are less affected by regional housing supply constraints.<sup>3</sup> Finally, use of gross directional population flows allows an examination of the differential importance attached to potential human capital spillover benefits and other migratory incentives by different migrant strata, as is useful for welfare evaluation.

We apply the model to place-to-place population flow data computed from the 1995 one-percent national population survey in China. The use of this dataset is motivated in part by its unique stratification of population flows by demographic and educational attributes, which facilitates assessment of the internal migration consequences of spatial inequality in human capital concentration. More importantly, this dataset reflects the migration choices of population strata during a dynamic period of rising labor mobility, skill-based wage premia, and regional economic disparities in China. The early 1990s coincides with Deng Xiaoping's push for economic reforms and a turning point in China's integration with the global economy. Foreign direct investment (FDI) was the primary source of technology transfer associated with acceleration in China's manufacturing exports during that period, as evidenced in part by the surge in FDI between 1991 and 1995 (Fig. 1). That same period was marked by an increasing awareness of the value of knowledge and skills; as shown in Zhang et al. (2005), the return to schooling in Chinese cities rose from about 4% in 1988 to 10% in 2001, with most of the rise occurring post-1992. Hence opportunities to upgrade human capital became important among the determinants of migratory incentives. We therefore expect destination human capital concentration to be valued both for its impact on employment opportunity and for its spillover benefits to human capital investment. We further account for regional concentration of FDI as an additional incentive for investment in human capital, which would be more profitable in places of large and rapid technological change. Despite the perceived value of human capital investment, the lack of institutional development in China posed serious impediments to human capital investment by migrant workers. In particular, low-skill migrant workers in Chinese cities often were denied formal jobs, had little social and employment security, and lacked education opportunities for themselves or their children (*e.g.*, Wang and Zuo, 1999). Few low-skill migrants, therefore, were motivated to invest in their human capital, given their limited long-term prospects in the cities, nor were they assisted in doing so.<sup>4</sup>

Research findings suggest that spatial variation in human capital agglomeration played a salient role in explanation of disparate regional growth trajectories in China. Upon accounting for regional differentials in skill-based compensation, cost-of-living, and amenities, we find that high-skill migrants attached significant importance to human capital concentration in destination regions. This finding suggests migratory benefits arising from human capital spillover for high-skill workers. However, as expected, low-skill migrants do not appear to benefit from co-locating with high-skill workers. Accordingly, disparate migratory incentives across skill-based strata may have served to restrain regional skill convergence in China (Luo and Zhu, 2008).

The plan of the paper is as follows. We provide additional background on Chinese internal labor migration and regional economic development in Section 2. Section 3 presents the utility maximizing directional migration model applied to China's stratified place-toplace migration odds data. The labor migration and regional socioeconomic and amenity data are described in Section 4. Section 5 discusses identification issues and provides evidence of skill-based selectivity in migration choices. We conclude and highlight the welfare and policy implications of the empirical findings in Section 6.

## 2. Chinese internal labor migration background and literature

In the three decades of central planning prior to 1980, labor migration in China was directed by national economic development plans (see World Bank, 2009, p.154). A large wave of rural-to-urban migration occurred during the 1950s in the context of China's early industrialization. In the 1960s and 1970s and as a consequence of China's Cultural Revolution, labor migration was driven by relocation of coastal industries to interior provinces and by assignment of educated urban youth to rural farms. This second wave of labor migration sought to reduce regional inequality in human capital concentration. The economic recovery and reform that took place during the 1980s and in the aftermath of the Cultural Revolution was accompanied by reverse migration of large numbers of previously relocated skilled coastal workers and youth to their home cities. At the same time, rural village and township enterprises (TVEs) sought to encourage rural surplus workers to remain in the countryside, and restrictive rural-to-urban migration policies, via a system of household residential registration (Hukou), continued to hinder efficient urban agglomeration in China (Au and Henderson, 2006).

The 1990s were characterized by economic liberalization and elevated population mobility. The privatization of state-owned enterprises and the inflow of FDI created strong growth in private-sector employment in Chinese cities. Also, the liberalization of the land market (Fu and Somerville, 2001) and the privatization of state housing (Fu et al., 2000) allowed considerable expansion of private-sector housing opportunities. Both reforms resulted in elevated labor migration to cities. Li

<sup>&</sup>lt;sup>1</sup> See, *e.g.*, Borjas et al. (1992); Chiswick (1999); Chiquiar and Hanson (2005); Dahl (2002); Davies et al. (2001); Gabriel et al. (1995); and Hunt and Mueller (2004).

<sup>&</sup>lt;sup>2</sup> Although the prior studies often use instruments to deal with potential endogeneity of human capital concentration with respect to the urban performance indicators, the endogeneity problem remains if the instruments are not orthogonal to unobserved locational heterogeneities in productive and consumption amenities that also influence the urban performance indicators (Henderson, 2007; Glaeser and Gottlieb, 2009).

<sup>&</sup>lt;sup>3</sup> Gyourko et al. (2006) show in the case of housing-supply-constrained San Francisco, productivity and amenity shocks result in little population growth but notable changes in population mix as high-skill workers move in to outbid low-skill workers with relatively low willingness to pay for place-specific amenities.

<sup>&</sup>lt;sup>4</sup> Employment and social discrimination against migrant workers in Chinese cities have been widely reported in news media; see, *e.g.*, "Survey: China" *The Economist*, April 6th, 2000; "Migration in China: Invisible and heavy shackles." *The Economist*, May 6th, 2010 (print edition).

(2004) estimates that inter-provincial migration totaled about 11 million people during the first half of the 1990s; also, twice that number moved within provinces. Zhang and Song (2003) estimate that about 70% of China's urban population growth during the 1990s derived from net migration. Accordingly, the level of urbanization in China increased by about 1 percentage point a year from 28% in 1990 to 33% in 1995 (Shen, 2005).<sup>5</sup>

China's vast rural-to-urban population flow has been the focus of numerous studies (see, for example, Johnson, 2003; Zhao, 1999, 2003). Liang and White (1997), Wu and Yao (2003) and Poncet (2006), for example, have demonstrated the increased responsiveness of inter-provincial migration flows during the 1980s and 1990s to regional disparities in employment opportunities and earnings. Other studies have documented increased income inequality between China's coastal and interior regions during the 1990s, which is attributed to economic policies and globalization that favored coastal regions (e.g. Fujita and Hu, 2001; Démurger et al., 2002). In addition, extant welfare analysis of rural-urban migration largely focuses on the impact of migration on consumption and investment in rural origins (e.g. Zhao, 2002; De Brauw and Rozelle, 2008; De Brauw and Giles, 2008). In contrast, migrant prospects in destination cities and the role of agglomeration economies, including those associated with human capital spillovers, have received substantially less attention in assessment of China inter-regional migration and regional economic development. It is to those issues that we now turn.

## 3. A directional migration odds model

We use a utility-maximizing framework to describe individual place-to-place migration choice. Let a resident of type k in region i derive utility  $U_{k,ij}$  from migration to region j. We assume that the utility is a linear function of relevant economic and amenity conditions in the origin and destination regions, denoted by a vector  $\mathbf{z}_{ij}$ ; thus,

$$U_{k,ij} = \mathbf{z}_{ij}\mathbf{\beta}_k + \boldsymbol{\omega}_{k,ij},\tag{1}$$

where  $\beta_k$  is a conforming vector of utility coefficients, which may vary depending on the type of resident indexed by k, and  $\omega_{k,ij}$  is a random disturbance. Assume N alternative destination regions. The probability that this individual migrates to region j (including j = i), denoted by  $\pi_{k,ij}$ , is

$$\pi_{k,ij} = \operatorname{Prob}\left(U_{k,ij} > U_{k,is}\right) \quad \text{for all } s \neq j.$$

$$\tag{2}$$

McFadden (1973) has shown that when the *N* disturbances are independent and follow identical Weibull distribution,<sup>6</sup> the probability in Eq. (2) is a conditional logit function:

$$\pi_{k,ij} = \frac{\exp(\mathbf{z}_{ij}\boldsymbol{\beta}_k)}{\sum\limits_{i=1}^{N} \exp(\mathbf{z}_{ij}\boldsymbol{\beta}_k)}.$$
(3)

Direct estimation of the conditional logit function of  $\pi_{k,ij}$ , as in Davies et al. (2001), is complex because  $\pi_{k,ij}$  depends on the vector  $\mathbf{z}_{ij}$  for all potential destinations. A simpler approach, found in Gabriel et al. (1987), Gabriel et al. (1993), Poncet (2006) and Sasser (2010), is to estimate the function of the migration odds ratio  $\pi_{k,ij}/\pi_{k,ii}$ , which describes the probability of an individual in region *i* moving to region *j*, relative to that of staying put:

$$\frac{\pi_{k,ij}}{\pi_{k,ii}} = \exp(\mathbf{Z}_{ij}\mathbf{\beta}_k).$$
(4)

In Eq. (4)  $\mathbf{Z}_{ij} \equiv \mathbf{z}_{ij} - \mathbf{z}_{ii}$  measures the relevant origin and destination conditions and  $\mathbf{Z}_{ij}\beta_k$  represents the net benefit of migration for type-*k* residents.  $\mathbf{Z}_{ij}$  would include origin conditions that push or discourage migration, origin–destination differential "pull" conditions, the expected cost of migration between origins and the destinations, and fixed effects for origins and destinations to control for unobserved location heterogeneities. The migration odds ratio can be computed empirically using place-to-place population flows over a given time period. Let  $m_{k,i}$ , be the population of type-*k* residents in region *i* at the beginning of the period,  $m_{k,ij}$ , the number of them migrating to region *j* during the period, and  $m_{k,ii}$ , the number remaining in region *i*. Then, for a large enough  $m_{k,i}$  we should have  $\pi_{k,ij}/\pi_{k,ij}/\pi_{k,ij}/(m_{k,i}\pi_{k,ii}) = m_{k,ij}/m_{k,ii}$ . Furthermore, following extant studies, we apply a log linear transformation to Eq. (4), substituting the migration odds ratio our linear regression equation<sup>7</sup>:

$$\ln\left(\frac{m_{k,ij}}{m_{k,ii}}\right) = \mathbf{Z}_{ij}\mathbf{\beta}_k + \varepsilon_{k,ij},\tag{5}$$

where  $\varepsilon_{k,ij}$  is a residual error.

We apply the above directional migration regression to a unique dataset of place-to-place population flows fully stratified by education attainment and age. The stratification enables an examination of how migration motives and costs vary across different population groups. To facilitate such examination, however, it is helpful to impose a structure on the way  $\beta_k$  varies across the population strata. We assume that the education and age effects are additive so that the importance of the average age effect across the education strata can be separately estimated; hence, for education group *e* and age group *a*, the directional migration regression equation is:

$$\ln\left(\frac{m_{e,a,ij}}{m_{e,a,ii}}\right) = \mathbf{Z}_{ij}(\boldsymbol{\beta}_e + \boldsymbol{\beta}_a) + \boldsymbol{\varepsilon}_{e,a,ij}.$$
(6)

Our analysis is similar to Hunt and Mueller (2004) in that we seek to account for both migrant selectivity as well as the tradeoff among wage and non-wage motives of migration. Hunt and Mueller (2004) employ individual-level data, which allow them to use a nested logit specification where the individual skill and demographic attributes affect the upper-level choice of whether or not to migrate but the location attributes influence the lower-level choice of migration destinations. Our analysis based on population flow statistics precludes a nested logit specification but allows a more reliable examination of the location effects based on a large population sample.

# 4. Data and variables

Our place-to-place population flow statistics are derived from the 1995 One-percent Population Survey conducted by the Chinese Government (see National Population Survey Office, 1997). The survey covers all 30 provincial-level jurisdictions in China (including 22 provinces, 5 autonomous regions and 3 provincial level cities). In this study, we refer to these 30 jurisdictions as provinces. Within each province, the survey randomly sampled one-third to one-half of the county-level jurisdictions. Altogether, more than 12 million people were sampled.

The 30 provinces vary considerably in population size. Tibet, located in the southwest high plateau, was the least populated region with just 2.2 million people in 1990, whereas Sichuan, located in the fertile upper-Yangzhi-River basin, was the most populous of China's provinces with over 100 million people. Per-capita income also varied considerably, from RMB 654 Yuan in the southwest province of Guizhou to RMB 4822 Yuan in Shanghai, the emerging economic powerhouse at the mouth of

<sup>&</sup>lt;sup>5</sup> The accuracy of official urban population statistics is impaired by the exclusion of new rural migrants to cities. Shen (2005)'s estimation of urban population adjusts for such undercounting.

<sup>&</sup>lt;sup>6</sup> The Weibull distribution has a cumulative distribution function F ( $\omega$ ) = exp ( $-e^{-\omega}$ ).

<sup>&</sup>lt;sup>7</sup> We handle the problem of censored value of the empirical migration odds ratio between relatively distance origins and destinations in our sample due to limited sample size  $m_{k,i}$  by adding a constant of  $1 \times 10^{-6}$  to the dependent variable  $m_{k,ij}/m_{k,ii}$ .

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#### Table 1

Distribution of migration flows between rural and urban areas (1995 Population Survey, including migration both within and across provinces). Source: Zhang et al. (1998). Table 1.

Origin (1990	Destination (1	995 residing place)		
residing place)	Urban district	County-level cities	Rural counties	Total
Urban district	1.8%	1.0%	1.7%	4.5%
County-level cities	5.3%	10.3%	1.9%	17.5%
Rural counties	41.8%	17.6%	18.7%	78.0%
Total	48.8%	28.9%	22.3%	100%

Yangzhi River in the east.<sup>8</sup> These provinces, except Tibet, form the set of alternative origins and destinations in our place-to-place migration analysis. We exclude Tibet from our analysis as it was largely isolated from the rest of the Chinese economy during our sample period due to the lack of transportation links. These 29 provinces are grouped into seven geographic regions according to geographic and economic similarities (these regional groupings are listed in column 2 of Appendix A). In general, per-capita income is lower in the western interior and rises with proximity to the east coast.

For this study, province-to-province population-flow matrices were constructed using the survey sample first sorted into strata by gender, age and schooling. For each stratum, the population-flow statistics  $m_{k,ij}$ ,  $i, j = 1, \dots, 29$ , are defined as the number of people residing in region j in 1995 (for no less than 6 months) whose regular residence 5 years earlier (in 1990) was in region *i* (the origin region). Accordingly, our analysis is based on the first comprehensive and statistically-based estimates of directional migration by socio-economic strata available for modern China. The rates of inter-provincial migration in our sample of economically active population (aged 15 to 65) are shown in the last two columns in Appendix A. Note that the data reveal limited provincial level variability in rates of out-migration, relative to a preponderance of in-migration to a few fast-growing provinces. The four biggest winners in terms of population gain as a percentage of their 1990 population were Beijing (the national capital in the northern coastal region), Shanghai (the emerging commercial center of China in the southern coastal region), Guangdong (a leading area of economic liberalization in the coastal south), and Xinjiang (a far northwestern province with a rich resource base). Overall, about 1.14% of the population migrated beyond their original province during the 5 year period. Zhang et al. (1998) show that household migration during this period was predominately rural-to-urban; in that regard, urban-to-rural migration (from both urban districts and county-level cities) accounted for only 3.6% of all migrants, whereas rural-to-urban migration accounted for nearly 60% of all population moves (see Table 1). Overall, about 78% of the migrants chose urban destinations; urban destinations are likely more dominant among inter-provincial moves, which are the object of our analysis.

Table 2 shows the distribution of the sample population by age and educational attainment. Our sample of economically active persons (aged 15 to 65) in the one-percent National Population Survey consists of about 8.4 million people, of which 52% are below age 35. The majority of the population did not complete high school (about 49% had at most a primary school education and whereas 36% had completed middle school). Note as well that the younger age group (below age 35) had a higher education attainment level than the older group. Furthermore, the table shows that the younger and more educated groups were more mobile (higher average migration odds ratios) as well as more selective in their migration destinations (higher standard deviation in migration odds). The table also reports the correlation in directional migration odds between population strata, to show the similarity in migration pattern between these strata. The bottom education strata appear to follow very different spatial pattern of migration than the population with at least middle school education, as indicated by the low correlation coefficients. Similar to Hunt and Mueller (2004), we find relatively small differences in migration pattern by gender; the correlation in directional migration odds between the gender groups is 0.81 for the bottom education strata and 0.92 for those attained at least middle school education. For simplicity, we focus our analysis of the directional migration pattern on the age and education based population strata as shown in Table 2.

Table 3 provides sample statistics of the explanatory variables used in  $Z_{ij}$ , where origin–destination (o–d) differences are calculated as the destination value minus the origin value of the variables. We report the mean absolute value and the standard deviation of each variable (the mean values of o–d difference variables are necessarily zero). Except the return-to-schooling measures, the variables in  $Z_{ij}$  are reflective of the regional characteristics as of 1990, the beginning of our sample period. The value and the data source for these provincial-level variables are listed in Appendix A.

The first three variables in  $\mathbf{Z}_{ij}$  reflect origin conditions that push or discourage people to move. Since the majority of inter-regional migrants are of rural origin, rural farming conditions (indicated by the amount of arable land per rural resident) are an important push factor. A higher level of arable land per rural resident would contribute to higher farming productivity and hence reduce incentives for rural residents to leave. Similarly a higher level of rural industrial employment opportunities (indicated by the share of rural workforce employed by township and village enterprises, or TVEs), would diminish the incentive for rural workers to migrate. The origin urbanrural economic gap (indicated by urban-to-rural ratio of per capita consumer spending) reflects rural-urban segregation (Wei and Wu, 2001), which hampers the mobility of rural unskilled workers but at the same time would push the more educated to leave.

We employ a number of controls for origin-destination bilateral differences in real income to account for migration incentives and choice of destination. Since the large majority of migration destinations in our sample are urban, these bilateral measures pertain to the urban sector in the origin and destination regions. Differential wage rates and skill premia (returns to schooling) between origin and destination urban sectors allow for specification and test of the Roy (1951) hypothesis in the context of China's sizable labor migration.<sup>9</sup> Cost of living differences are proxied by urban per capita consumer spending, which should be positively correlated with both household income and local cost of living. We further compute a regional temperature severity index (defined as the square root of the sum of the lowest temperature squared and the highest temperature squared) to reflect regional climatic amenities; a high value of this index indicates that the province has a more severe temperature either in the winter or in the summer or both. We would expect provinces with a temperate climate (hence a relatively low temperature severity) to be more attractive to migrants. We also include the size of the regional urban workforce as an indicator of destination employment opportunities. In addition, the availability of housing in the destination region, indicated by average housing space per person, is included to further differentiate cost of living between alternative destinations.

The empirical specification includes a bell-shaped distance function to capture the variable cost of migration, which is assumed to increase with migration distance at an increasing rate for short distances but at a decreasing rate for long distances. The variable cost not only reflects the pecuniary transport cost of relocation but also the cultural and information gaps that tend to be significantly higher once an individual moves beyond

<sup>&</sup>lt;sup>8</sup> In 1995, 1 US dollar buys 8.35 RMB at the official exchange rate.

<sup>&</sup>lt;sup>9</sup> The wage rates represent the average wage of employees in urban firms in 1990 and are not adjusted for potential differences in skill mix across regions. To address this issue, we estimate provincial-level returns to schooling using a sample of residents in 90 cities across the provinces derived from 1997 Urban Household Survey (see Appendix B). Our preference would have been to compute returns to schooling using earlier sample. Unfortunately, that data was not available. Regardless, the 1997 estimate of returns to schooling migrants. Note further that returns to schooling have been rising across Chinese cities since the 1980s, in the wake of economic reforms and China's integration into the global economy (see, e.g. Zhang et. al. 2005).

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Table 2	
Sample size and sample statistics of migration odds ratio by pop	ulation strata.

Education level	Age group	Sample size	% total sample	Odds rati	0	Correlation in	n directiona	l migration o	odds	
				Mean	Std dev.	Primary scho	ol	Middle s	chool	High school
Primary school or below	15-34	1,495,764	17.8%	0.056%	0.164%	Age 15-34	35-65	15-34	35-65	15-34
	35-65	2,612,208	31.1%	0.016%	0.061%	0.55				
Middle school	15-34	2,117,577	25.2%	0.074%	0.310%	0.42	0.33			
	35-65	918,346	10.9%	0.034%	0.164%	0.18	0.37	0.79		
High school or above	15-34	774,493	9.2%	0.108%	0.402%	0.26	0.34	0.92	0.82	
-	35-65	481,854	5.7%	0.061%	0.401%	0.07	0.17	0.82	0.90	0.87

Note: The sample size refers to the number of observations in the 1995 One-percent Population Survey. The odds ratio and the correlation statistics are based on 812 observations of origin-destination pairs for each education-age stratum.

#### Table 3

16

0.346

Sample statistics of explanatory variables (29 origin by 28 destination provinces, 812 observations).

Variables							М	ean absolute va	alue	Standard deviat	
1	Origin lo	og farm land pe	er rural resident				0.	626		0.584	
2	Origin to	ownship & villa	ige enterprise ('	TVE) share of ru	Iral workforce		0.	137		0.135	
3	Origin u	rban-rural log	per capita cons	umer spending	differential		0.	337		0.161	
4	o-d diffe	erential: log ur	ban wage rate				0.	152		0.193	
5	o-d diffe	erential: urban	return to schoo	oling			0.	018		0.023	
6	o-d diffe	erential: per ca	pita urban cons	umer spending			0.	356		0.461	
7	o-d diffe	erential temper	rature severity				2.	723		3.740	
8	o-d diffe	erential: log ur	ban workforce s	size			0.	771		1.003	
9	Destinat	ion log housing	g space per pers	son			2.	937		0.199	
10	negative	exponential o	-d distance squ	ared, $exp(-d_{ii}^2/d_{ii})$	100)		0.	311		0.294	
11	o-d diffe	erential: FDI sh	are of fixed inv	estment	,		0.	105		0.150	
12	o-d diffe	erential: share	of urban popula	tion with high	school or abov	e education	0.	069		0.090	
13			io, primary scho				0.	030		0.083	
14	o-d mig	ration odds rat	io, middle scho	ol (%)			0.	052		0.145	
15	o-d migration odds ratio, high school or above (%)							072		0.159	
	0	Mean years of schooling of o-d migration flow								4 5 5 0	
16	Mean ye	ears of schoolin	g of o–d migrat	ion flow			8.	767		1.573	
16	5	ears of schoolin coefficients	g of o–d migrat	ion flow			8.	767		1.573	
16 Variables	5		g of o–d migrat	ion flow 5	6	7	8	9	10	1.573	12
	Correlation	coefficients	0 0		6	7			10		12 - 0.165
Variables	Correlation	coefficients 3	4	5	-		8	9		11	
Variables	Correlation 2 - 0.267	coefficients 3	4	5	-		8	9		11	
Variables 1 3	Correlation 2 - 0.267 0.168	coefficients 3 0.569	4	5	-		8	9		11	
Variables 1 3 4	Correlation 2 -0.267 0.168 -0.429	coefficients 3 0.569 -0.190	4 0.166	5	-		8	9		11	
Variables 1 3 4 5	Correlation 2 - 0.267 0.168 - 0.429 - 0.326	coefficients 3 0.569 -0.190 -0.146	4 0.166 0.108	5 0.040	-		8	9		11	
Variables 1 3 4 5 6	Correlation 2 -0.267 0.168 -0.429 -0.326 -0.624	coefficients           3           0.569           - 0.190           - 0.146           - 0.240	4 0.166 0.108 0.633	5 0.040 0.289	0.059		8	9		11	
Variables 1 3 4 5 6 7	Correlation 2 -0.267 0.168 -0.429 -0.326 -0.624 -0.624 -0.162	coefficients           3           0.569           -0.190           -0.146           -0.240           -0.058	4 0.166 0.108 0.633 - 0.149	5 0.040 0.289 0.210	0.059	-0.230	8	9		11	
Variables 1 3 4 5 6 7 8	Correlation 2 - 0.267 0.168 - 0.429 - 0.326 - 0.624 - 0.162 - 0.179	coefficients           3           0.569           -0.190           -0.146           -0.240           -0.058           0.190	4 0.166 0.108 0.633 - 0.149 - 0.182	5 0.040 0.289 0.210 0.156	0.059 0.376 0.180	-0.230	8	9		11	
Variables 1 3 4 5 6 7 8 9	$\begin{array}{c} \hline Correlation\\ \hline 2\\ \hline -0.267\\ 0.168\\ -0.429\\ -0.326\\ -0.624\\ -0.162\\ -0.179\\ -0.006\\ \end{array}$	coefficients           3           0.569           -0.190           -0.146           -0.240           -0.058           0.190           0.023	4 0.166 0.633 -0.149 -0.182 -0.016	5 0.040 0.289 0.210 0.156 -0.024	0.059 0.376 0.180 0.038	-0.230 0.273 0.058	8 0.082 0.322	9 0.021		11	
Variables 1 3 4 5 6 7 8 9 10	$\begin{tabular}{c} \hline Correlation \\ \hline 2 \\ \hline 0.168 \\ - 0.429 \\ - 0.326 \\ - 0.624 \\ - 0.162 \\ - 0.179 \\ - 0.006 \\ 0.086 \end{tabular}$	coefficients           3           0.569           -0.190           -0.146           -0.240           -0.058           0.190           0.023           -0.154	4 0.108 0.633 - 0.149 - 0.182 - 0.016 0.000	5 0.040 0.289 0.210 0.156 -0.024 0.000	0.059 0.376 0.180 0.038 0.000	-0.230 0.273 0.058 0.000	8 0.082 0.322 0.000	9 0.021 0.137	-0.130	11	
Variables 1 3 4 5 6 7 8 9 10 11	$\begin{tabular}{c} \hline Correlation \\ \hline 2 \\ \hline 0.267 \\ 0.168 \\ - 0.429 \\ - 0.326 \\ - 0.624 \\ - 0.162 \\ - 0.179 \\ - 0.006 \\ 0.086 \\ - 0.209 \end{tabular}$	coefficients           3           0.569           - 0.190           - 0.146           - 0.240           0.058           0.190           0.023           - 0.154           0.196	4 0.166 0.108 0.633 - 0.149 - 0.182 - 0.016 0.000 0.335	5 0.040 0.289 0.210 0.156 -0.024 0.000 0.163	0.059 0.376 0.180 0.038 0.000 0.372	-0.230 0.273 0.058 0.000 0.147	8 0.082 0.322 0.000 0.037	9 0.021 0.137 0.099	-0.130	<u>11</u> 0.377	
Variables 1 3 4 5 6 7 8 9 10 11 12	$\begin{tabular}{ c c c c c } \hline \hline Correlation \\ \hline \hline 2 \\ \hline 0.267 \\ 0.168 \\ - 0.429 \\ - 0.326 \\ - 0.624 \\ - 0.162 \\ - 0.179 \\ - 0.006 \\ 0.086 \\ - 0.209 \\ - 0.333 \end{tabular}$	coefficients           3           0.569           - 0.190           - 0.146           - 0.240           - 0.058           0.190           0.023           - 0.154           0.196           - 0.488	4 0.166 0.108 0.633 - 0.149 - 0.182 - 0.016 0.000 0.335 0.419	5 0.040 0.289 0.210 0.156 -0.024 0.000 0.163 0.288	0.059 0.376 0.180 0.038 0.000 0.372 0.587	-0.230 0.273 0.058 0.000 0.147 0.186	8 0.082 0.322 0.000 0.037 - 0.323	9 0.021 0.137 0.099 -0.274	-0.130 0.000 0.000	<u>11</u> 0.377 0.043	-0.165

-0.067Note: Origin-destination (o-d) differences are calculated as the destination value minus the origin value.

-0.014

0.167

-0.171

0.001

the adjacent provinces. Specifically, the distance-related disincentive of migration is computed as  $\exp(-(d_{ii}/d_0)^2)$ , where  $d_{ii}$  is the direct distance between the capitals of the origin and the destination provinces as measured on a map and  $d_0$  is chosen to be 10 (36th percentile value of  $d_{ij}$  across the 29 origin and destinations) to maximize the statistical significance of the distance-related disincentive. A constant is included in  $\mathbf{Z}_{ij}$  to allow for a fixed cost of migration that must be offset for migration to be profitable.

0.373

The key regional attribute included in  $Z_{ij}$  for the purpose of this study is the bilateral difference in the share of regional urban population with high school or above education.<sup>10</sup> This measure of regional concentration of human capital can influence migratory incentives via its effect on skilled-based wage compensation, consumer amenities, and cost of human capital accumulation. Although the primary focus of this study is not to isolate these alternative channels of influence, note that we do control for regional differences in skill-based wage compensation and amenities in the analysis. We further control for regional differences in foreign direct investment concentration (FDI share of cumulative fixed investment over 1990-1993 at official exchange rates), to account for the potential productivity-growth effect of technology change and knowledge spillovers to different migrant strata.<sup>11</sup> Accordingly, in this analysis, the share of educated urban population seeks to proxy for non-wage incentives associated with regional human capital concentration. Regional human capital concentration averages about 16% in 1990 in our sample. Regional FDI concentration is about 6% on average.

-0.224

0.066

-0.160

-0.116

Despite the fact that the independent variables in  $\mathbf{Z}_{ii}$  are constructed mostly to reflect regional conditions as of 1990, prior to the migration phenomenon we examine, spatial equilibrium theories tell us that these variables are not necessarily exogenous in the presence of

<sup>&</sup>lt;sup>10</sup> Shapiro (2006) finds the human capital spillover effects in the context of US metropolitan employment growth to derive from urban concentration of college graduates rather than high-school graduates. However, share of college graduates in Chinese regional population was less than 3% on average in 1995.

<sup>&</sup>lt;sup>11</sup> The role of FDI in augmenting host region productivity growth in developing economies is widely documented (e.g., Mastromarco and Ghosh, 2009; Tuan et al., 2009). Mastromarco and Ghosh (2009) find that productivity spillover effects of FDI depend positively on local concentration of human capital, suggesting complementarities between human capital and knowledge spillovers.

unobserved locational heterogeneities that may influence observed regional conditions in 1990. We therefore seek to control for the unobserved locational heterogeneities by including regional fixed effects in the directional migration regression. However, certain restrictions on the location fixed effects are necessary in order for the effects of bilateral social economic differences to be identified. Except for the distance-related measure of migration cost, these bilateral variables are perfectly correlated with the full set of both origin and destination fixed effects. Accordingly, in our baseline estimation, we include the origin and destination fixed effects at the level of the seven broad geographic regions (as shown in column 2 of Appendix A). We then examine the robustness of these bilateral effect estimates with less restrictive specifications of the destination fixed effects.

The lower panel of Table 3 displays a matrix of correlation coefficients between the variables in  $\mathbf{Z}_{ij}$ . Origin rural farm land per capita is negatively correlated with rural industrialization, but is positively correlated with rural-urban per-capita spending disparities. The positive but moderate correlation between regional wage-rate differential and the differential per-capita consumer spending indicates regional differences in cost of living; indeed, the variance of the spending differentials is much greater than that of the wage-rate differential. Regions with higher FDI level and human capital concentration are more productive but offer lower real income (these two concentration measures are more strongly correlated with cost of living than with wage rates), indicative of the non-wage benefits of FDI and human capital spillovers; those correlation coefficients are consistent with Roback's (1982) compensating-variation principle of spatial equilibrium. Interestingly, more temperate regions (with lower temperature severity) are not compensated with lower real income (the temperature severity index is positively correlated with the cost of living but somewhat negatively correlated with wage rates). Regions with a larger urban sector do not appear more productive but appear to value skill more highly (offering higher returns to schooling). Finally, regions with a relatively higher urban concentration of high-school graduates offer somewhat higher returns to schooling, possibly reflecting the skill complementarities in employment as suggested by Giannetti (2003) and Berry and Glaeser (2005).<sup>12</sup>

In addition, the lower panel of Table 3 provides the simple correlations between migration odds and the variables in  $\mathbf{Z}_{ij}$ . Note that migration odds are somewhat positively correlated with o–d differential wage rates and housing space per person but slightly negatively correlated with the o–d differential with respect to high-school graduate share of urban population. We also observe some degree of skill-based selectivity in migration choices with respect to migration distance. Skill-based selectivity is also evidenced in o–d differentials with respect to urban workforce size, FDI level, and returns to schooling. Further, mean years of schooling of migration flows are elevated among more distant destinations as well as destinations with relatively low temperature severity (more favorable climate) and lower shares of more highly educated urban populations. We turn next to the examination of the marginal effects of the independent variables  $\mathbf{Z}_{ij}$  on the size and mix of the directional migration flows.

## 5. Estimates of the directional migration incentives

We estimate a system of equations for directional migration odds corresponding to the six education (primary-school education or below, middle-school education, and high-school education or above) by age (15–34 and 35–65) strata, as described by Eq. (5), using the GMM method with cross-section White covariance. We use 28 origin province fixed effects and 28 destination province fixed effects, in addition to the distance-related migration cost, *i.e.*,  $\exp(-d_{ij}^2/100)$ , as instruments. These instruments over-identify the independent variables but help to mitigate the potential influences of unobserved location heterogeneity on model estimates by minimizing the covariance of the residuals with all the origin and destination fixed effects.

Our baseline regression assumes that education and age effects on migration incentives are additive as described in Eq. (6). We account for unobserved regional heterogeneity by including fixed effects associated with the seven broad regions. We restrict the origin region fixed effects to be common for all education and age strata but allow the destination region fixed effects to vary by education and by age, on the grounds that the migration outflows across origin provinces are much less variable than migration inflows across destinations as shown in Appendix A. The baseline estimates are reported in Table 4, where Panel 2 controls for regional differences in skilled-based wage compensation and Panel 1 does not, so as to help the assessment of the importance of wage incentives versus non-wage incentives attached to various destination regional attributes.

We focus our discussion on the results shown in Panel 2, which provides an interesting picture of skill-based selectivity in labor migration during a period of rapid technological change and rising labor market returns to skills in Chinese cities. Three variables account for origin conditions that influence migration outflow. The availability of origin region farm land and employment opportunities in township and village enterprises (TVEs) significantly alter the incentive to migrate. More highly educated groups as well as younger groups appear to attach substantially less importance to rural employment opportunities but more importance to land resource availability. As expected, disparities in urban-rural per-capita consumption spending, reflecting a lack of urban-rural economic integration in the origin region, differentially affect the migratory propensities of population by education strata. Large gaps between same region rural and urban spending depress the migration odds of low-skill rural workers, who might be more financially constrained to migrate, but spur out-migration among more highly educated groups who are able to seek more distant opportunities.

We include other controls for destination housing availability, which influences migration inflow, and migration pecuniary and nonpecuniary costs, which are assumed to vary with distance. Higher destination average urban living space per person serves to significantly enhance migration to those areas. The propensity to migrate declines with distance between origin and destination regions. While this finding conforms to the literature more generally, note that here we specify the relationship to take a bell-shaped form,  $\exp(-d_{ij}^2/100)$ , which provides improved explanatory power relative to a negative exponential or quadratic form. Moreover, as would be expected, for higher human capital migrants for whom the expected economic return on migration is elevated, the adverse effect of distance on migratory propensities is damped, relative to coefficients estimated for lower educational attainment strata.

The next set of controls accounts to migratory incentives attached to origin-destination differential conditions. Our results show that the urban wage-rate differential between destination and origin regions is positive and highly significant in the determination of the propensity to migrate and destination choice; as expected, the effect is somewhat smaller in magnitude for low-skill migrants and for older migrants. Older migrants have a shorter time frame over which to discount pecuniary returns associated with a move, as do low-skill migrants whose chance of establishing a career in cities is often limited. Further, our estimates support the Roy (1951) hypothesis in the context of a major emerging market economy. Migration to places with relatively higher returns-toschooling is damped among migrants with only a primary school education; in marked contrast, migration to those same provinces by more highly educated migrants is significantly elevated. Further, upon accounting for regional differences in wage incomes, differences in per capita urban consumer spending reflect the differential urban cost of living between destination and origin provinces, which work to significantly damp migration; the size of those effects is a fraction of that of the wage-rate effects, consistent with the share of non-traded goods in total consumption.

<sup>&</sup>lt;sup>12</sup> Positive social returns to human capital (productivity externalities) are widely documented; Rauch (1993) and Moretti (2004), for example, show that proximity to human capital raises individual earnings. Ciccone and Peri (2006), however, find the wage spillover effects to be not robust under a downward-sloping local demand for skills. Acemoglu (1996) also shows that the observed social returns could arise from pecuniary externalities alone.

	: baseline estimates.
	ration odds model:
	l migration
	f the directional
5 4	1 estimates of
Table	GMIV

Independent variables	Panel 1				Panel 2			
	Primary school or below Middle school	/ Middle school	High school or above Age 35–65	Age 35–65	Primary school or below Middle school	Middle school	High school or above Age 35-65	Age 35–65
Origin log farm land per rural resident	-0.723 (3.1) <sup>***</sup>	-0.767 (3.7)***		0.379 (5.0)***		-0.802 (3.9)***	-0.831 (4.2)	0.376 (4.8)***
Origin TVE share of rural workforce	$-4.463(5.9)^{***}$	$-3.960(6.4)^{***}$		$-1.547(4.3)^{***}$	$-3.955(5.1)^{***}$	$-3.145(4.9)^{***}$	$-0.989(1.9)^{*}$	$-1.461(3.8)^{***}$
Origin urban-rural log per capita consumer spending differential 0.806 (1.2)	tial 0.806 (1.2)	$2.975(5.2)^{***}$	$4.602(8.1)^{***}$	$1.346(4.9)^{***}$	-0.528(0.8)	$2.089(3.5)^{***}$	$3.727 (6.3)^{***}$	$1.420(5.1)^{***}$
Destination log housing space per person	$3.397 (8.5)^{***}$	$3.683 (11)^{***}$	$2.986(10)^{***}$	0.238 (1.0)	$3.790(9.6)^{***}$	$3.850 (11)^{***}$	$3.231(11)^{***}$	0.013 (0.1)
$\exp(-d_{ij}^2/100)$	$4.143(23)^{***}$	$3.917(26)^{***}$	$3.430(24)^{***}$	0.174 (1.6)	$4.169(23)^{***}$	$3.870(26)^{***}$	$3.483(24)^{***}$	0.139 (1.2)
Origin-destination differentials:					1000	-to the		
Log urban wage rate					$1.880(3.3)^{***}$	$2.329(4.6)^{***}$	$2.358(4.8)^{***}$	$-1.340(4.6)^{***}$
Urban return to schooling						1.060(0.4)	$4.927(1.8)^{*}$	2.654 (1.5)
Per capita urban consumer spending	$0.444(1.8)^{*}$	-0.024(0.1)		$-0.898(7.1)^{***}$		$-0.962(3.3)^{***}$	$-1.078(4.0)^{***}$	$-0.372(2.3)^{**}$
Temperature severity	$-0.051(2.2)^{**}$	$-0.115(5.6)^{***}$		-0.016(1.3)	-0.016(0.6)	$-0.085(3.7)^{***}$	-0.097 (4.0) <sup>***</sup>	$-0.069(4.7)^{***}$
Log urban workforce size	$0.315(3.8)^{***}$	$0.598(8.9)^{***}$	-	$0.079(1.7)^{*}$	$0.239(2.8)^{***}$	$0.540(8.0)^{***}$	$0.614(9.8)^{***}$	0.129 (2.7)***
FDI share of fixed investment	$5.587(6.4)^{***}$	6.467 (8.1) <sup>***</sup>	$10.38(13)^{***}$	0.565 (1.4)	$3.770(3.9)^{***}$	$4.989(5.7)^{***}$	$9.067(10)^{***}$	$1.642(3.6)^{***}$
Share of urban population with high school or above education		$2.797(3.1)^{***}$	$4.422(5.6)^{***}$	$5.471(9.0)^{***}$	$-3.673(3.3)^{***}$	$3.207(3.4)^{***}$	$4.977(5.8)^{***}$	$4.788(7.6)^{***}$
Constant		$-20.35(20)^{***}$	$-18.27(20)^{***}$	$-2.510(3.8)^{***}$	$-19.71(17)^{***}$	$-20.57(20)^{***}$	$-18.90(20)^{***}$	$-1.854(2.8)^{***}$
o-d fixed effects	Common 6 origin effects and 6 destination effect for each education level and one	s and 6 destination	effect for each educa	tion level and one		nd 6 destination e	ffect for each education	level and one age
	age group (total 30 fixed	fixed effects)			group (total 30 fixed effects)	tts)		
Adjusted Age 15–34	0.218	0.321	0.349		0.239	0.341	0.245	
R-squared Age 35–65	0.258	0.257	0.249		0.263	0.257	0.245	
Note: The regression equations are $\ln(m_{e,a,ij}/m_{e,a,ij},w) = \mathbf{Z}_{ij}(\mathbf{B}_e + \mathbf{B}_a) + \varepsilon_{e,a,ij}$ , where the dependent variable is the log of migration odds ratio (plus 1×10 <sup>-6</sup> ) for each of the six education-age strata, $\mathbf{P}_a$ for age 15–34 is set to zero. The equations are jointly estimated using Eviews GMM method with cross-section White covariance. The instruments include exp( $-d_{ij}^2/100$ ) and the fixed effects for 28 origin provinces and 28 destination provinces. The number of observations is 812 (29 origins by 28 destinations). <i>I</i> -statistics are in parentheses: <sup>*******</sup> denote statistical significance at 18, 5% and 10% level respectively. <i>I</i> statistics are 0.551 and 0.564, respectively, for Panel 1 and 2.	$+\beta_a) + \varepsilon_{e,a,jj}$ , where the deperection White covariance. The section White covariance are set is the statistical signal $+s^*$ , $+s^*$ , denote statistical signal $+s^*$ .	ndent variable is th instruments incluc nificance at 1%, 5%	the log of migration odd the exp( $-d_{ij}^2/100$ ) and and 10% level respect	ts ratio (plus 1 × 10 the fixed effects fo ively. J statistics ar	ependent variable is the log of migration odds ratio (plus 1×10 <sup>-6</sup> ) for each of the six education-age strata, <b>B<sub>a</sub></b> for age 15–34 is set to zero. The equations The instruments include exp( $-d_0^2/100$ ) and the fixed effects for 28 origin provinces and 28 destination provinces. The number of observations is 812 (29 significance at 1%, 5% and 10% level respectively. J statistics are 0.551 and 0.564, respectively, for Panel 1 and 2.	ation-age strata. A destination provii ely, for Panel 1 ar	a for age 15–34 is set to nces. The number of obs nd 2.	zero. The equations ervations is 812 (29

Seasonal temperature extremes, indicative of a less amenable climate, appear to discourage movement by more educated and older groups, but have little effect on moves by low skill migrants. This result is similar to the findings in Hunt and Mueller (2004) and reflects a greater willingness to pay for climate amenities by higher skilled population strata. The destination-origin region differential in the size of the urban workforce, as a measure of labor market opportunities associated with the relative scale of the provincial urban job markets, exerts notably more positive effects on place-to-place migration for individuals with more schooling and work experience, indicating the importance of the labor-market pooling benefits for skilled workers. In addition, the destination FDI concentration draws migrants across education and age strata and, interestingly, the draw is considerably stronger for the top education stratum.

Turning to the benefits of human capital agglomeration, we find that regional concentration of human capital has a substantial but asymmetric influence on the migration destination choices of different educational strata. Whereas migrants in the top educational stratum appear to be strongly encouraged to move to regions with high concentrations of human capital, those in the bottom stratum appear to be discouraged from making such a choice. Consequently, in the wake of global economic integration of Chinese cities, increased internal labor mobility served to reinforce regional variation in human capital concentration, in turn contributing importantly to the widening regional disparities in economic development in China. While disparate regional growth trajectories in China are often attributed to location advantages or policy bias (Fujita and Hu, 2001; Démurger et al., 2002), our results indicate the importance of migrant self-selection so as to reinforce differential regional trajectories in human capital agglomeration.

Comparing Panels 1 and 2, note, as expected, that the migration effects of per capita urban consumer spending differentials are much more positive in Panel 1, where wage differentials are not accounted for. The values of other controls are modestly affected by the inclusion of the skill-specific wage differentials in the regression. The effects of origin-destination differences in regional climate, labor market pooling, and FDI concentration are somewhat weaker after accounting for wage differentials, suggesting that differences in those regional amenity and economic factors are partly but not fully compensated by skill-specific wage differences. Upon accounting for skill-specific wage differences, the effect of regional human capital concentration becomes somewhat weaker for low education and older migrants households but somewhat stronger for the more educated migrants. Overall, regional climatic amenities, urban labor market pooling, FDI concentration and human capital concentration continue to contribute importantly to migratory incentives upon controlling for wage differentials.<sup>13</sup>

As shown in Table 4, the chi-squared tests for the I statistics of the GMM estimates reject the hypothesis that the over-identification conditions are satisfied. In other words, the explanatory variables in the model do not fully capture the regional heterogeneities encompassed by the GMM instruments. We provide further robustness analysis of the GMM estimates against alternative controls of origin and destination fixed effects in the regression. Those results are reported in Appendix C. In Panel A, we relax the assumption that the education and age effects are additive as well as allow the 12 origin and destination regional fixed effects to vary across the 6 educate and age strata. As shown, the general pattern of skill-based selectivity in migratory choices evidenced in Table 4 is robust to the more detailed estimates in Panel A. We note that the regional fixed effects vary more significantly among the destinations than the origin regions but appear quite highly correlated across

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<sup>&</sup>lt;sup>13</sup> It is unlikely that the much of the influence of the regional human capital concentration on migratory incentives, as well as the effects of regional climate, labor market pooling, and FDI concentration, are due to deficiencies in quality-adjustment of regional wage compensation. As a robust check, we used the human capital adjusted wage rates derived from the 1997 Urban Household Survey (see footnote 9) in place of the average urban wage rate. The former measure of urban wage rate differential turns out to have much weaker explanatory power than the latter. Other estimates are largely robust to variations in the definition of the urban wage rate measure.

education and age strata. A chi-squared test based on I statistics fails to reject the hypothesis of additive effects of education and age on model coefficients at 5% statistic significance level.<sup>14</sup> In Panel B, we assume the origin and destination fixed effects to be common across the education and age strata but we expand the destination fixed effects to cover all the 29 different provinces (28 destination fixed effects in addition to the constant). Also, the destination housing availability control is omitted as it is now accounted for by the expanded destination fixed effects. Except that the effects of urban labor market pooling are damped and those of returns to schooling considerably upward revised, the other estimates and the general pattern of skill-based selectivity in migration choices are robust to the inclusion of expanded destination fixed effects. In particular, migrants in the top education stratum are strongly attracted to regions with high human capital concentration, in contrast to these in the bottom education stratum, who appear to be discouraged from migrating to high human capital regions. In Panel C, we apply the Equation Weighted Least Square (WLS) estimator to the directional migration model in Panel B without the over-identification instruments employed in the GMM estimator. We obtain fairly consistent results.

In summary, we find the differential migratory effects among educational strata to be both significant and robust to the inclusion of skillspecific wage rates and origin and destination region fixed effects. Our results are consistent with findings that human capital concentration is important to metropolitan economic growth (e.g., Glaeser et al., 1995; Glaeser and Shapiro, 2003; Glaeser et al., 2011; Gennaioli et al., 2011). Our findings further suggest that studies based on crosssectional regressions of net population flows may underestimate the migratory effects of metropolitan human capital concentration, as the migratory responses of low-skill workers may offset the inflow high-skill workers to high-human-capital places. Results indicate that high-skill workers attach significant importance to destination human capital concentration in their migratory choices-as a 1 percentage point increase in the share of urban population with at least high-school education in the destination province raises the migration odds to the province of the top education stratum by almost 5% (from the base migration odds). That magnitude of effect is similar to that of an additional percentage point of returns to schooling and suggests substantial benefits to human capital agglomeration in Chinese cities. These benefits seem to arise, not only from social returns to human capital that help to raise the productivity of skilled workers (see footnote 12), but also from human capital spillover effects that aid in individual human capital accumulation and productivity growth, as the high-skill migrants in our sample value the destination human capital concentration in addition to regional differences in returns to schooling.

As suggested above, our findings also point to the existence of important impediments to human capital investment among low-skill migrants to Chinese cities, who are found to attach little importance to destination human capital concentration. Low-skill migrants enjoy little social and employment security in cities and typically have no access to public services, including public education (Wang and Zuo, 1999). Their chance of successfully settling in cities is low and so too is their motivation to invest in human capital. Furthermore, the informal employment and housing of low-skill migrants considerably limit their opportunities for social interactions and human capital spillovers with high-skill workers. Were social interactions and employment opportunities in cities unhindered for lowskill workers, one might expect them to attach greater importance to human capital spillover benefits as the low-skilled are more likely to learn from the high-skilled in social interactions and to reap elevated returns to human capital investment. Indeed, Glaeser (1999) and Lucas (2004) assume that benefits to social interactions in cities accrue primarily to the less skilled. Further, Duleep and Regets (1999) show that internal migrants in the United States with a greater skill gap at their destinations invest more in learning. The absence of human capital agglomeration benefits among low-skill migrants, according to the endogenous growth model of Lucas (2004), thus would contribute to widening skill gaps among Chinese population and represent important welfare losses associated with China's internal labor migration. Indeed, income inequality in Chinese cities has widened since the early 1990s: the income Gini coefficient, according to World Bank (2009), rose from 0.335 in 1990 to 0.469 in 2004.

# 6. Conclusions

In this paper, we undertake analyses of internal labor migration in China during the 1990s. That period was characterized by liberalization of labor markets, rising returns to skills, and accelerating urbanization. We focus on the role of human capital agglomeration in determination of migration choices and regional economic disparities. Research findings indicate that more educated households were more mobile and more selective in their migration choices. These households attached greater importance to destination amenities, labor market pooling, technological change, and notably, human capital concentration, even after accounting for regional differences in skill-specific wage compensation. The mobility choices of high human capital households, therefore, appeared to have reinforced the disparate regional distribution of human capital. The finding that regional human capital concentration attracts mostly skilled workers helps to explain the failure of labor migration over recent decades to alleviate persistent regional disparities in Chinese economic development.

Whereas increasing geographic concentration of human capital need not be detrimental to national economic growth when human capital is scarce and can be more productively employed through agglomeration (Henderson, 2003), the study finding that low-skill workers attach little importance to destination human capital concentration, and appear unlikely to locate in high human capital zones, remains a cause for concern. Modern economic development theories emphasize the instrumental role labor migration plays in enabling skill upgrading via human capital spillovers from high-skill to proximate lower-skilled workers (Lucas, 2004). The apparent exclusion of low-skill migrants from the benefits of human capital spillovers reflects in part institutional short-comings associated with Chinese urbanization that impedes human capital investment by low-skill migrants. Removal of those impediments has become crucial to sustaining the momentum of Chinese economic growth but remains a challenge to Chinese policymakers.<sup>15</sup> By articulating welfare issues pertinent to labor migration in China, this present study may also serve to demonstrate the usefulness of modern theories of growth and development to normative analysis of migration in a development context. Such discussion is lacking in extant literature (Lall et al., 2006).<sup>16</sup>

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 $<sup>^{14}</sup>$  We test the restriction that the coefficients of the top 13 variables in Panel C can be reduced to 3×13 coefficients for the education strata plus 13 coefficients for the older age stratum. The probability for the null hypothesis to hold according to chi-squared distribution is 9.7%.

<sup>&</sup>lt;sup>15</sup> Political resistance to reforms to remove such impediments remains strong, although the reform issues recently surfaced to the forefront of the policy debate during the National People's Congress held in March 2010; See, *e.g.*, Financial Times report "Beijing Edges Towards Residence Reform" (March 5, 2010, available online at http:// www.ftchinese.com/story/001031584/en) and The Economist report "Migration in China: Invisible and heavy shackles" (May 6th, 2010, print edition).

<sup>&</sup>lt;sup>16</sup> In the traditional development literature, absent controls for human capital accumulation, unchecked rural-urban migration is often found to have negative welfare impact, as demonstrated by Harris and Todaro (1970). Recently Fan and Stark (2008) show that, in the presence of human capital externalities on labor productivity, migration of skilled rural labor to cities may lower the average human capital level in both origin and destination locations, resulting in a downward shift in productivity for all workers. In contrast, the modern development literature emphasizes the importance of human capital accumulation for economic growth and the role of migration in raising private incentives to invest in human capital through harnessing human capital spillover effects.

# Appendix A. Provincial economic indicators

		arable land 1990 (mu) <sup>1</sup>	village enterprise share of rural workforce <sup>1</sup>	p.c. consumer spending ratio, 1990 <sup>1</sup>	wage rate, 1990 (yuan/month) <sup>1</sup>	return to schooling <sup>4</sup>	consumer spending, 1990 (yuan/month.) <sup>1</sup>	temperature (Celsius) <sup>1</sup>	workforce 1990 (10,000) <sup>1</sup>	space per person (sq.m.) <sup>2</sup>	1990–93 cumulative fixed investment <sup>1</sup>	population with at least high school education <sup>3</sup>	of 1990 popula-tion <sup>2</sup>	of 1990 popula-tion <sup>2</sup>
Beijing	CN	1.02	48.0%	1.61	2,653	8.58%	1,548	-15.0/37.6	454.9	20.8	7.8%	31.0%	1.32%	7.16%
Tianjing	CN	1.68	43.4%	1.79	2,438	8.77%	1,310	-13.0/36.9	284.3	16.0	8.1%	22.8%	1.00%	3.03%
Hebei	CN	2.16	9.6%	1.43	2,019	5.16%	664	-12.2/38.5	652.7	20.4	2.8%	13.9%	0.80%	1.01%
Liaoning	CN	2.7	21.6%	1.68	2,180	6.50%	1,074	-24.3/32.0	1,012.2	16.8	7.7%	14.9%	0.56%	
Shandong	CN	1.48	16.1%	1.32			681	-13.5/37.5	767.5	20.7	8.0%	10.9%	-	
Shanghai	CS	1.12	58.0%	1.51	2,917	6.70%	1,908	-5.2/39.6	508.1	22.0	15.2%	28.2%		
Jiangshu	CS	1.38	24.1%	1.07	2,129	6.23%	841	-6.5/40.0	879.9	27.0	9.8%	11.4%	0.80%	
Zhejian	CS	0.91	17.3%	1.02	2,220	5.64%	912	-4.1/40.3	476.0	32.3	4.4%	9.0%	1.43%	
Fujian	CS	0.95	13.8%	1.18	2,162	4.37%	837	4.0/41.7	310.9	22.9	27.9%	10.0%	0.91%	
Guangdong	CS	1.04	14.3%	1.14	2,929	5.09%	972	4.1/37.8	785.5	17.8	23.1%	11.8%	0.49%	4.42%
Hainan	CS	1.17	3.5%	1.39	1,982	7.85%	708	7.4/38.6	105.9	15.1	23.7%	24.7%	1.86%	
Inner	NE	6.76	5.5%	1.43	1,846	4.60%	703	-25.3/33.7	369.7	13.6	1.2%	16.6%	1.27%	1.41%
Mongolia														
Jilin	NE	4.82	9.2%	1.51	1,888	5.82%	882	-27.3/33.0	517.3	15.9	3.6%	17.0%	1.23%	0.62%
Heilongjian	NE	7.46	10.9%	1.71	1,850	6.19%	918	-25.9/34.2	856.2	15.3	2.1%	18.1%	1.75%	0.65%
Shanxi	NC	3.07	14.2%	1.34	2,111	5.97%	607	-20.2/33.4	438.7	18.1	1.3%	15.3%	0.56%	0.67%
Henan	NC	1.58	7.4%	1.26	1,825	6.62%	499	-9.4/36.8	692.6	19.6	1.9%	12.0%	1.02%	0.38%
Shannxi	NC	2.6	7.7%	1.49		8.66%	614	-9.0/39.3	379.2	18.4	3.5%	17.5%	0.93%	0.60%
Anhui	SC	1.58	7.3%	1.18	_		588	-6.3/40.3	484.8	19.1	2.5%	10.2%	1.63%	0.34%
Jiangxi	SC	1.33	7.0%	1.30	1,729		652	-2.1/39.5	386.1	20.8	3.9%	12.9%	1.76%	
Hubei	SC	1.45	11.3%			4.97%	759	-2.5/39.6	698.5	24.3	5.0%	17.4%	-	
Hunan	SC	1.16	8.1%	1.32		5.18%	666	-4.5/40.6	551.0	26.1	4.1%	11.7%		
Guangxi	SW	1.16	2.9%				576	-0.8/37.0	311.8	16.0	11.2%	14.8%		
Sichuan	SW	1.13	6.2%		2	6.15%	616	0.55/37.6	936.1	24.5	2.8%	8.1%		0.44%
Guizhou	SW	1.21	1.8%	1.10		3.43%	445	-3.4/33.5	225.5	15.8	1.6%	13.0%	1.62%	
Yunnan	SW	1.54	4.2%	1.39		4.51%	628	-0.9/30.3	291.9	19.0	1.2%	12.3%	0.81%	0.69%
Gansu	ΝW	3.17	6.2%	1.76		7.71%	552	-12.8/34.3	231.9	15.4	0.3%	14.7%	1.27%	0.72%
Qinghai	ΝW	2.71	4.6%	1.86	2,632	1.53%	786	-20.0/30.7	66.4	10.6	0.2%	20.2%		1.33%
Ningxia	ΝW	3.48	5.6%	1.41	2,252	6.42%	634	-21.2/34.4	67.4	15.5	0.6%	17.7%		1.19%
Xinjiang	ΝW	4.06	6.5%	1.89		7	904	-22.8/34.1	300.6	18.5	0.5%	33.2%	-	4.24%
Coefficient of	74.2%	100%	16.3%	19.0%	27.3%	38.7%		57.6%	26.7%	115%	38.8%	44.7%	157%	
variation														

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# Appendix B. Estimates of returns to schooling by provinces

Variable	Coeff	Variable	Coeff	Variable	Coeff
	(t-stat)		(t-stat)		(t-stat)
MALE	0.159 (19)***	Zhejian	$-0.029(3.5)^{***}$	Hubei	-0.036 (10)***
EXPYEAR	0.013 (4.7)***	Fujian	-0.042 (4.5)***	Hunan	$-0.034(4.5)^{***}$
EXPYEAR <sup>2</sup>	0.000 (0.3)	Guangdong	-0.035 (4.6)***	Guangxi	$-0.022(2.8)^{***}$
YSCH	0.086 (25)***	Hainan	-0.007(0.5)	Sichuan	$-0.024(3.9)^{***}$
Constant	7.820 (156)***	Inner Mongolia	$-0.040(10)^{***}$	Guizhou	-0.051 (14)***
Provincial dummy × YSCH		Jilin	$-0.028(7.3)^{***}$	Yunnan	$-0.041(14)^{***}$
Tianjing	0.002 (0.2)	Heilongjian	-0.024 (3.0)***	Gansu	-0.009(0.9)
Hebei	-0.034 (4.2)***	Shanxi	-0.026 (3.3)***	Qinghai	-0.070 (3.1)***
Liaoning	$-0.021(3.1)^{***}$	Henan	-0.020 (2.1)**	Ningxia	-0.022(1.3)
Shandong	$-0.027(3.2)^{***}$	Shannxi	0.001 (0.1)	Xinjiang	-0.040 (11)***
Shanghai	$-0.019(1.9)^*$	Anhui	$-0.044(5.0)^{***}$	89 city fixed effects	
Jiangshu	-0.023 (2.9)***	Jiangxi	$-0.030(3.1)^{***}$	R-squared	0.386

Note: The dependent variable is ln(*Employment Income*). The sample is from 1998 Urban Household Survey and includes 117664 individuals from 90 cities across 29 provinces. *MALE* is a dummy variable equal to unity for males, *EXPYEAR* is the number of years of working experience, and *YSCH* is the number of years of schooling of the individual. *t*-statistics are in parentheses and \*\*\*, \*\*, \* denote statistical significance at 1%, 5% and 10% level respectively.

# Appendix C. Robustness analysis of the directional migration odds model estimation

Independent variables				F	Panel A (	GMM)			
	Ag	je 15–34				Age 35-6	65		
		imary sch. below	Middle school	High sch. or above		Primary s or below		Middle school	High sch. or above
Origin log farm land per rural resider Origin TVE share of rural workforce Origin urban-rural		0.496 (1.5) 5.443 (5.4) <sup>***</sup> 3.287 (3.6) <sup>***</sup>	$\begin{array}{r} -0.369\ (1.5)\\ -3.429\ (4.5)^{***}\\ -0.631\ (0.9)\end{array}$	-0.892 (4.2) -1.535 (2.5) 5.450 (8.5) <sup>*</sup>	$5)^{\uparrow\uparrow}$	-0.471 ( -4.894 ( -0.451 (	(5.8)***	-0.476 (1.6) -3.065 (3.8) <sup>***</sup> 1.934 (2.2) <sup>**</sup>	$\begin{array}{c} -0.380~(1.1)\\ -5.477~(6.7)^{***}\\ 5.299~(5.7)^{***}\end{array}$
log per capita consumer spending of Destination log housing space per pe $\exp(-d_{ij}^2/100)$	rson 4.4	444 (9.1) <sup>***</sup> 456 (20) <sup>***</sup>	3.873 (10) <sup>***</sup> 3.772 (23) <sup>***</sup>	$2.678\ {(8.4)}^{*}$ 2.989 ${(19)}^{*}$	***	4.160 (9. 4.096 (22	6) <sup>***</sup> 2) <sup>***</sup>	3.964 (8.4) <sup>***</sup> 4.027 (19) <sup>***</sup>	3.384 (6.9) <sup>***</sup> 3.559 (16) <sup>***</sup>
Origin-destination differentials: Log urban wage rate Urban return to schooling Per capita urban consumer spendir Temperature severity Log urban workforce size FDI share of fixed investment	ng — 0.0 0.0	053 (3.9)*** 9.560 (2.6)*** 1.984 (4.8)*** 004 (0.1) 065 (0.6) 499 (2.1)**	4.241 (7.1)*** - 3.485 (1.2) - 2.090 (6.2)*** - 0.074 (2.8)*** 0.381 (5.0)*** 2.453 (2.5)***	$\begin{array}{r} 2.915 \ (5.6)^3 \\ 13.51 \ (4.2)^3 \\ & -1.045 \ (3.5)^3 \\ & -0.107 \ (4.0 \\ 0.582 \ (8.2)^3 \\ 5.371 \ (5.6)^3 \end{array}$	5) <sup>***</sup> )) <sup>***</sup>	2.348 (3. -2.842 ( -1.940 ( -0.076 ( 0.300 (3. 1.939 (1.	(0.9) $(5.2)^{***}$ $(2.6)^{***}$ $(4)^{***}$	3.554 (4.6)*** 8.126 (2.3)** - 1.356 (3.3)*** - 0.114 (3.3)*** 0.251 (2.5)** 3.106 (2.4)**	$\begin{array}{c} 2.137 \ (2.6)^{***} \\ 12.074 \ (3.3)^{***} \\ -2.013 \ (4.8)^{***} \\ -0.134 \ (3.6)^{***} \\ 0.626 \ (6.0)^{***} \\ 8.201 \ (5.3)^{***} \end{array}$
Share of urban population with hig or above education	h school 0.2	238 (0.2) 20.72 (14) <sup>***</sup>	2.455(2.3) $3.778(3.6)^{***}$ $-20.07(17)^{***}$	3.993 (4.4) <sup>*</sup>	***	-22.24 (	0)***	(2.4) $(4.859 (3.8)^{***}$ $(-22.57 (15)^{***}$	$(5.3)^{***}$ 11.13 $(8.6)^{***}$ -21.22 $(14)^{***}$
Constant o-d fixed effects Origin: Coastal South Origin: Northeast Origin: Central North Origin: Central South Origin: Southwest Origin: Northwest Destination: Coastal South Destination: Northeast Destination: Central North Destination: Central South Destination: Southwest Destination: Northwest Adjusted <i>R</i> -squared	0.1 	20.72 (14) 209 (0.8) 0.043 (0.2) 0.289 (1.1) 563 (1.7)* 412 (0.9) 269 (0.6) 1.322 (4.9)*** 2.101 (7.3)*** 2.241 (9.0) 2.315 (8.8)*** 2.324 (6.7)*** 009 (0.3) 343	$\begin{array}{c} -20.07\ (17)^{***}\\ 0.642\ (2.2)^{**}\\ -0.036\ (0.2)\\ -0.229\ (1.1)\\ 0.772\ (2.8)^{***}\\ 0.940\ (2.6)^{***}\\ 0.213\ (0.6)\\ -0.635\ (3.1)^{***}\\ -1.142\ (5.1)^{***}\\ -1.546\ (7.3)^{***}\\ -1.576\ (6.4)^{***}\\ 0.457\ (1.7)^{*}\\ 0.363\end{array}$	$\begin{array}{c} 1.600 \ (6.6)^3\\ 0.356 \ (1.9)^3\\ - \ 0.356 \ (2.7)\\ 0.289 \ (1.3)\\ - \ 1.042 \ (3.3)\\ 0.076 \ (0.3)\\ * \ - \ 0.585 \ (3.6)\\ * \ - \ 0.422 \ (2.3)\\ * \ - \ 1.408 \ (5.6)\ (5.6)\$	<pre>     ***     2)** 3)*** 3)*** 3)*** 7)*** 7)*** 7)*** </pre>	$\begin{array}{c} 0.221 \; (0.\\ 0.050 \; (0.\\ - \; 0.449 \; (0.\\ 0.377 \; (1.\\ 0.796 \; (2.\\ - \; 0.998 \; (2.\\ - \; 0.996 \; (0.\\ - \; 1.577 \; (0.\\ - \; 2.004 \; (0.\\ - \; 2.073 \; (0.\\ - \; 2.073 \; (0.\\ - \; 1.601 \; (0.\\ 0.497 \; (1.\\ 0.308 \; (0.\\ - \; 0.\\ -$	7) 2) 2.0)** 4) 0)** 3)** 4.1)*** 5.8)*** 8.8)*** 8.6)*** 5.4)***	$\begin{array}{c} -22.57 \ (15)^{***} \\ -0.300 \ (1.2) \\ -0.693 \ (2.7)^{***} \\ 0.326 \ (1.1) \\ 0.390 \ (0.9) \\ 0.406 \ (1.0) \\ -0.773 \ (3.0)^{***} \\ -0.925 \ (2.9)^{***} \\ -1.767 \ (6.7)^{***} \\ -1.767 \ (6.7)^{***} \\ -1.581 \ (4.5)^{***} \\ 0.576 \ (1.9)^{*} \\ 0.291 \end{array}$	$\begin{array}{c} -21.22\ (14) \\ \hline \\ 1.634\ (4.5) \\ ^{***} \\ 0.662\ (2.4) \\ ^{**} \\ 0.095\ (0.3) \\ 0.095\ (0.3) \\ 0.137\ (0.3) \\ 0.139\ (0.3) \\ -0.420\ (1.7) \\ ^{*} \\ -1.539\ (5.5) \\ ^{***} \\ -1.923\ (7.3) \\ ^{***} \\ -1.803\ (5.9) \\ ^{***} \\ -1.345\ (4.0) \\ ^{***} \\ -0.009\ (0.0) \\ 0.295 \end{array}$
Independent variables	Panel B (GMM) Primary school or below	Middle school	High school or above	Age 35–65	Panel C Primary or belov	school	Middle school	High school or above	Age 35-65
Origin log farm land per rural resident Origin TVE share of rural workforce Origin urban-rural log per capita consumer spending differential $\exp(-d_{ij}^2/100)$	$\begin{array}{r} -1.297~{(6.4)}^{***}\\ -4.597~{(5.0)}^{***}\\ 0.356~{(0.5)}\\ 4.299~{(26)}^{***}\end{array}$	$\begin{array}{c} -1.549 \left( 8.4 \right)^{***} \\ -4.093 \left( 4.9 \right)^{***} \\ 3.079 \left( 4.5 \right)^{***} \\ 3.924 \left( 28 \right)^{***} \end{array}$	$-2.543(3.3)^{***}$	$\begin{array}{c} 0.545 \ (7.7)^{***} \\ - \ 0.459 \ (1.4) \\ 1.051 \ (3.9)^{***} \\ - \ 0.217 \ (2.1)^{**} \end{array}$	-1.109 -6.342 -0.546 4.455 (2	(7.7) <sup>****</sup> (0.8)	-1.357(7.5) -5.010(6.6) $1.195(1.9)^{2}$ $3.933(22)^{*}$	$5)^{***} - 1.784 (2.4)^{*}$ * 3.712 (6.0) <sup>***</sup>	* 0.282 (2.0)** * 0.159 (0.3) 1.359 (2.7)*** * -0.295 (1.6)
Origin–destination differentials: Log urban wage rate Urban return to schooling per capita urban consumer spending Temperature severity Log urban workforce size	1.585 (2.3) <sup>**</sup> 5.217 (1.3)	2.117 (3.3)*** 12.879 (3.5)*** - 1.639 (3.5)*** - 0.073 (2.5)**	2.547 (3.9)***	- 1.234 (4.9)*** 6.016 (3.8)*** 0.202 (1.4) - 0.043 (3.7)*** - 0.053 (1.3)	1.879 (2 2.845	(0.8) $(4.8)^{***}$	2.217 (3.4) <sup>3</sup> 6.592 (2.1) <sup>3</sup> -1.914 (4.5 -0.062 (2.3	*** 2.552 $(4.0)^{***}$ ** 14.921 $(4.8)^{**}$ 5)*** -1.719 $(4.1)^{**}$	* $0.555 (2.1)^{**}$ * $-0.043 (2.2)^{**}$

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#### Appendix C (continued)

		Panel B (GMM)				Panel C (WLC)			
Independent va	ariables	Primary school or below	Middle school	High school or above	Age 35-65	Primary school or below	Middle school	High school or above	Age 35-65
		2.682 (2.4) <sup>**</sup> -3.317 (2.6) <sup>**</sup>	4.237 (4.0) <sup>***</sup> 1.063 (0.9)	7.503 (7.1) <sup>***</sup> 3.289 (2.9) <sup>***</sup>	0.557 (1.5) 1.950 (3.4) <sup>***</sup>	4.935 (4.7) <sup>***</sup> 0.460 (0.4)	5.818 (5.8) <sup>***</sup> 1.838 (1.7) <sup>*</sup>	7.431 (7.5) <sup>***</sup> 3.581 (3.3) <sup>***</sup>	-0.597 (0.9) 0.718 (0.7)
Constant	ove education	-8.442 (14)***	- 8.685 (15)***	-8.909 (15)***	-1.889 (22)***	-8.123 (16)***	-8.047 (16)***	-8.477 (17)***	* - 1.901 (11) <sup>**</sup>
o-d fixed effect	ts	Common 6 o (total 34 fixe	0	28 destination ef	fects	Common 6 c (total 34 fixe	0	28 destination ef	fects
Adjusted	Age 15-34	0.329	0.439	0.473		0.403	0.485	0.475	
R-squared	Age 35-65	0.383	0.331	0.321		0.393	0.369	0.341	

Note: The regression equations are  $\ln(m_{e,a,ij}/m_{e,a,ii}) = \mathbf{Z}_{ij}(\boldsymbol{\beta}_e + \boldsymbol{\beta}_a) + \varepsilon_{e,a,ij}$ , where the dependent variable is the log of migration odds ratio (plus  $1 \times 10^{-6}$ ) for each of the six education-age strata.  $\boldsymbol{\beta}_a$  for age 15–34 is set to zero. The equations are jointly estimated using Eviews GMM method with cross-section White covariance in Panel A and B and using Equation Weighted Least Squares (WLS) in Panel C. The GMM instruments include exp( $-d_{ii}^2/100$ ) and the fixed effects for 28 origin provinces and 28 destination provinces. J statistics are 0.422 and 0.534, respectively, for Panel A and B. The number of observations is 812 (29 origins by 28 destinations). t-statistics are in parentheses; \*\*\*, \*\*, \* denote statistical significance at 1%, 5% and 10% level respectively.

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