The Mechanics of Regional Growth: Evidence from a Large-Scale Skill Resettlement Program*

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Abstract

China compulsorily relocated millions of educated youth from urban to rural areas during the late 1960s and 1970s. About two million sent-down youth permanently settled in those rural areas. I study the effects of the Down to the Countryside Movement on regional economic outcomes in subsequent decades. An exogenous increase in the high-skilled population resulted in faster regional population and productivity growth in regions that experienced a positive human capital shock. I provide evidence that the growth effects worked through the arrival of more migrants, an increase in educational attainment, and shifts in the employment structure towards skill-intensive sectors.

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1 Introduction

China's Down to the Countryside Movement is arguably one of the largest skill resettlement programs in history. During the late 1960s to the 1970s, the Chinese government compulsorily displaced approximately 17 million educated young people from urban to rural areas. The displacement engulfed over 10 per cent of China's urban population at that time. After the end of the Movement, about 2 million sent-down youth permanently settled in those rural areas. This drastic movement permanently disrupted the geographic distributions of a generation of skilled population. In this paper, I study the effects of the Down to the Countryside Movement on regional economic outcomes in subsequent decades as well as the channels through which regional growth occurred.

The primary motivation of this Movement was to curb capitalist thinking that was prevalent in urban China during that period. By mobilizing and sending urban youth down to the countryside, Mao believed the urban youth could be "reeducated" by the poor and lower-middle peasants. Such a reeducation was ideological rather than academic, as the urban youth achieved much higher educational attainment than the peasants. Rural economic development was not an intended goal of this Movement.[1]

The Down to the Countryside Movement makes for a particularly interesting program for three reasons. First, the Movement resulted in a rare, large-scale internal redistribution of the skilled people across space. The Chinese case, which involved internal migration, contrasts with most of the historical episodes of human capital shocks examined in the literature, which have been associated with influxes of foreign immigrants (Rocha, Ferraz and Soares, 2017). Unlike advanced economies, such as the United States, Canada, or Australia, which attract high-skill immigrants from other countries, most developing countries achieve regional growth goals by inducing the internal migration of high-skilled people. In

[1] Some historical documents describe that the Movement also has the goals of reducing unemployment in urban areas and increasing agricultural productivity. However, this description is inconsistent with many facts: If it were to solve the unemployment among young people, why was almost *everyone* in some early cohorts sent down? Why were cohorts that graduated before the Movement not affected at all? If it were to increase agricultural productivity, why was the Movement a nationwide policy that affected all regions, rather than a policy that targeted specific areas that particularly lagged in agricultural productivity? Why were many educated youth sent down to regions that already insufficient arable land on the per capita basis?

this sense, the Down to the Countryside Movement case is relevant to developing countries. Second, debates about the impacts of labor supply shocks have focused on low-skill labor supply shocks (Monras, 2015; Dustmann, Schönberg and Stuhler, 2017). My analysis provides new evidence about high-skilled labor supply shocks. Third, the exogenous assignment of skills during the Movement provides plausibly causal evidence of the effects of human capital on regional growth, an identification problem that is difficult to tackle. I contribute to the literature unique causal evidence relevant to the themes examined by Shapiro (2006).

Despite being well known as an unprecedented skill resettlement program, relatively little is known about how the Movement impacted subsequent regional economic outcomes. This is probably because in order to accurately and consistently depict economic outcomes in China at granular geographic levels over an extended period of time, a great deal of data needs to be collected. I assemble these data from all six Chinese censuses from 1953 to 2010 and from additional sources such as province statistical yearbooks. Using the 1982 Census microdata, I construct a proxy for skill resettlement by comparing, on the one hand, the population shares of skilled people of the cohort that was impacted by the Movement and, on the other, an older cohort that was not impacted. The validity of this measure relies on the fact that the send-down movement was compulsory and was an unanticipated shock to all people, and therefore we can compare the impacted and unimpacted cohorts. My proxy, which I call the *skill resettlement rate*, is higher when a larger number of high-skilled people in the compulsorily relocated cohort reside in a prefecture relative to its population. In addition, the main regional outcomes I study include population growth and productivity growth.

My main empirical strategy compares regional outcomes across Chinese prefectures that exogenously lost or received different proportions of high-skilled people. By examining the administration of the send-down process as well as the settlement decisions of the sent-down youth, I show that the skill resettlement rate provides a novel and exogenous measure of the regional human capital shock.

Using the full sample of all Chinese prefectures, I find that an exogenous increase in the high-skilled population induced faster regional population growth in subsequent decades, but had no effect on regional productivity growth. The results are robust to controlling for geographic or infrastructure characteristics. My baseline estimate implies that, on average, an increase in skill resettlement rate by one standard deviation leads to a 2.04 percentage point increase in regional population growth rate per decade. This translates to an additional 6.25 percentage point population growth over three decades – an effect roughly equivalent to 18% of the population growth in China from 1982 to 2010.

I then explore heterogenous effects of the human capital shock by considering separately regions that received and lost educated youth. Receiving regions were generally more backwards, whereas losing regions were more advanced. I find positive effects on both population and productivity growths for receiving regions. On the other hand, the growth of advanced regions was not adversely impacted by their loss of educated youth. I emphasize a key feature of the sent-down policy that helps rationalize the heterogenous effects. Whereas educated urban youth were sent down during the Movement, physical capital investments did not follow because of the top-down nature of China's investment decisions. This finding points to the key role that physical capital plays in inducing regional growth, as others have noted in the literature (Kline and Moretti, 2013). As a result, advanced regions were able to leverage their abundance of physical capital despite their loss of human capital during the movement.

In addition, I investigate three channels through which the growth effects occurred. First, I find migration, rather than fertility, drives regional population growth as a result of the human capital shock. Second, positive human capital shock induce an increase in educational attainment, leading to a larger share of the regional population that achieves middle school and above. Third, I observe shifts in the employment structure towards more skill-intensive sectors as a result of the positive human capital shock. In particular, I find evidence that the most substantial growth concentrates in the manufacturing sector. This finding suggests the importance of structural transformation in regional growth, particularly in the context of a developing country that transitioned from a predominantly agricultural economy to an industrialized economy.

Related literature

This paper is related to the literature on the determinants and mechanisms of regional growth. The literature suggests regions exhibit vastly different rates of growth, both in the cross section and over time (as documented, e.g., in Blanchard and Katz, 1992). Understanding the mechanics of regional growth is important because such an understanding sheds light on the spatial evolution of economic activities and the persistence of regional inequalities. Glaeser et al. (1992) consider several characteristics of urban production structures. Glaeser and Saiz (2004) focus on the role of human capital. Several papers investigate the role of amenities, such as weather (Rappaport, 2007) and culture (Falck, Fritsch and Heblich, 2011). Duranton and Turner (2012) and Baum-Snow et al. (2017) consider roads and transportation as determinants. Bajo-Rubio, Díaz-Mora and Díaz-Roldán (2010) and Rodríguez-Pose, Psycharis and Tselios (2012) emphasize the importance of investments on regional growth, although both only with evidence from a select country. In addition, Davis and Weinstein (2002) study the geography of economic activity in light of three theories – increasing returns, random growth, and locational fundamentals. They find that locational fundamentals establish the relative spatial patterns, and increasing returns determine the degree of spatial differentiation. The literature has studied many potential drivers of regional growth, such as human capital, investments, and location fundamentals. However, as Duranton (2016) points out, with the exception of a few papers, much of the literature has so far focused on making the case for one particular driver of regional growth. This paper provides a general framework in which both human capital and physical capital are emphasized as key inputs of regional production, and regional growth works through channels of agglomeration, structural transformation, and changes in skill composition.

My paper also relates to the literature studying how regional economies respond to local labor supply shocks. A number of papers study the impact of the relative supplies of high and low skill labor on high and low skill wages (Katz and Murphy, 1992; Card and Lemieux, 2001; Card, 2009). Card (2009) estimates the impact of local labor supply on local wages in cities. It is harder to find convincing evidence of the effects on local economies of local labor supply shocks than labor demand shocks, largely because it is difficult to find "natural experiments" that exogenously shock local labor supply. Most papers in this literature examines the effects of foreign immigration on wages and employment rates of native workers in local labor markets. Dustmann, Schönberg and Stuhler (2017) exploit a commuting policy that led to a sharp and unexpected inflow of Czech workers to areas along the German-Czech border, and examine the impact of an exogenous immigration-induced labor supply shock on local wages and employment of natives. Monras

(2015) exploits an exogenous push factor that raised Mexican migration to the US due to the Mexican Peso Crisis, and evaluates the effects of the influx of Mexican immigrants on the wage dynamics in U.S. cities. The exogenous shocks in the literature are typically low-skilled, foreign migration. In contrast, my paper contributes to this literature by exploiting an exogenous shock of high-skilled, internal migrants.

A strand of literature studies the relationship between human capital and growth. The theoretical link between human capital and growth dates back to the early endogenous models, such as in Lucas (1988). This paper provides indirect evidence on the validity of the endogenous growth theory. Empirically, the strong association between human capital and economic growth has been noted both in studies of economic performance across countries (Barro, 1991), and across regions in the United States (Rauch, 1993; Simon, 1998) and in other countries (Simon and Nardinelli, 1996; Gennaioli et al., 2013). The literature also documents that human capital may have persistent impacts on regional growth (Shapiro, 2006; Rocha, Ferraz and Soares, 2017). Many papers investigate specifically the relationship between human capital and regional or city growth. Cities and regions with high concentrations of human capital tend to grow faster (Glaeser, Scheinkman and Shleifer, 1995; Gennaioli et al., 2013). In addition, the skill ratio of workers has been diverging across cities and regions in recent decades in some developed economies, a phenomenon known as "The Great Divergence" (Berry and Glaeser, 2005; Morreti, 2012; Diamond, 2016). These two facts suggest the spatial distribution of human capital may have persistent impacts on local economic outcomes, as well as on inequality across cities and regions. Although the majority of the literature focuses on developed countries, some papers provide evidence in the context of developing countries (Fleisher, Li and Zhao, 2010).

My paper also contributes to the literature that assesses place-based policies (Duflo and Pande, 2007; Kline and Moretti, 2013). A related literature consists of other papers on resettlement programs. Bazzi et al. (2016) uses a population resettlement program in Indonesia to study how location-specific human capital and skill transferability shape the spatial distribution of productivity. Beaman (2012) studies the social networks of refugees resettled in the United States and the dynamics of their labor market outcomes. Chetty, Hendren and Katz (2016) implement the Moving to Opportunity experiment and study the effects of exposure to better neighborhoods on children. In some of the resettlement papers, the outcome of interest is the outcome of an individual, whereas in my paper, the outcome of interest is regional growth. Evaluations of place-based policies consider both the benefits and costs of the policies. The Down to the Countryside Movement, however, is a compulsory resettlement program whose administration had no explicit costs.

The remainder of the paper proceeds as follows. Section 2 provides background on the Down to the Countryside Movement. Section 3 describes my data and measurements. Section 4 develops my estimation framework. Section 5 presents my main results. Section 6 investigates key channels of regional growth. Section 7 concludes.

2 Historical background

2.1 China's Down to the Countryside Movement

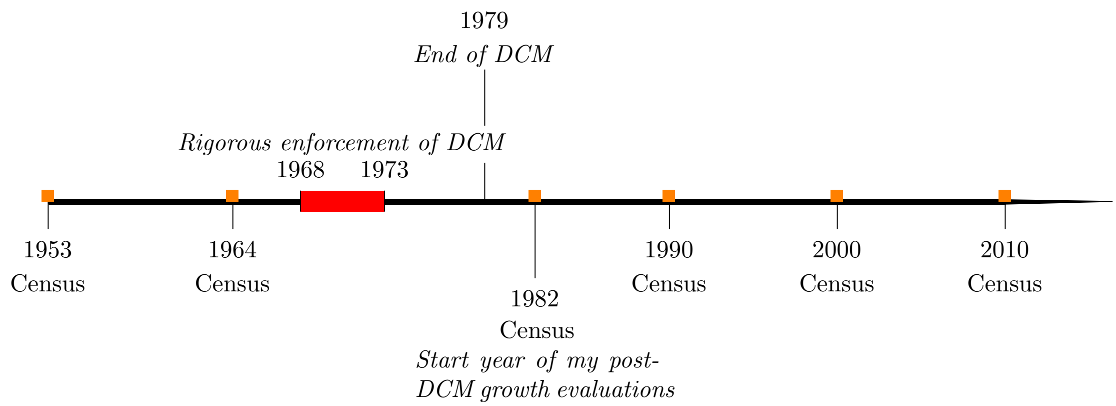
> *"The countryside is a vast expanse of heaven and earth; there one can display one's full talents."*
>
> – Mao Zedong

From the late 1960s to the 1970s, the Chinese government exiled millions of educated urban young people to the countryside. In December 1968, the Down to the Countryside Movement was initiated on a large scale, when Mao Zedong declared in a speech that "it is very necessary for the urban educated youth to go to the countryside to be re-educated by the poor farmers." (quoted in Zhang, Liu and Yung, 2007). The large-scale movement followed the initiation of the Cultural Revolution in 1966. The key motivation of the movement was to suppress capitalist thinking, which Mao perceived to be prevalent in urban China during the Cultural Revolution (Ebrey, 2006).

My study focuses on the most intensive period of the movement from 1968 to 1973 (Figure 1).[2] During this period, few exemptions from being sent down were

[2] In 1973, Mao organized a national conference to discuss the Down to the Countryside Movement, in response to the increasing resistance and resentment towards the send-down policy. The conference reoriented the policy to focus on short-distance relocations, and allowed more exemptions so that fewer people were sent down. In addition, sent-down youth started to expect their relocation to be temporary.

Figure 1: *A timeline of the Down to the Countryside Movement (DCM) and Chinese censuses*



Notes: The red bar covers the period of rigorous enforcement of the Down to the Countryside Movement (DCM) from 1968 to 1973. DCM ended in 1979. Every orange dot represents a census conducted in the corresponding year. This timeline includes all censuses conducted in China since the establishment of the People's Republic of China in 1949. The year 1982 is the starting point of my post-DCM growth evaluations.

allowed. People sent down during this period had no expectation that they could ever return home. The sent-down youth were expected to "put down roots" in the countryside (Liu, 1998, p. 164). They stayed in the countryside for an extended period of time; many of them settled there after the end of the movement.

Figure 1 is a timeline that shows the movement in relation to all six population censuses conducted in China since the establishment of the People's Republic of China in 1949. The censuses are my main data sources among many other data I use. The 1982 Census was the first census conducted after the movement.

More details about the Movement that are relevant for my identification strategy will be discussed in Section 4.

2.2 Educational reforms during the Cultural Revolution

One of the areas most radically affected by the Cultural Revolution (1966–1976) was China's educational system. The main educational reforms that took place during the Cultural Revolution are the following: school closures, length of education, and substance of education.

Children aged 7-9 began elementary schools around the times of the Cultural Revolution. Before the Cultural Revolution, China's education was on a 6-3-3 system, consisting of 6 years of elementary schools, 3 years of middle school, and 3 years of high school. However, the curriculum was shortened to be a 5-2-2 system. This short curriculum was abolished after the end of the Cultural Revolution. When the 5-2-2 curriculum system was in effect, typically all middle school students went on for high school education, and they were sent down upon graduation from high school.[3]

Soon after the Cultural Revolution started in mid-1966, all schools suspended normal operations. However, the closure of schools caused social unrest. Idle students became "Red Guards"[4] and spread the Cultural Revolution from schools through society. In response to the increasing social unrest, the central government issued the "Notice for Universities, Secondary Schools and Elementary Schools to Return to Class but Continue the Revolution" on October 14, 1967. Since then schools gradually started to reopen.

Two features of the school closure are particularly relevant for my study. First, schools started to reopen in October 1967, before the send-down movement in late 1968. As a result, some middle school graduates entered high schools. Contrary to common perception, the 1950-52 birth cohorts, who graduated from middle school from 1966-68, did have high school graduates. In addition, because of school closures, several cohorts delayed their secondary education. However, although there were years during which schools were shut down, all birth cohorts ended up having access to middle school and high school education on a delayed basis.[5] For example, the 1953 birth cohort graduated from elementary school in 1966, but weren't able to enter middle school until the end of 1968.

The substance of education also changed substantially during the Cultural Revolution. The curriculum focused on Maoist ideology, and factory and farm work. As a result, although many people had middle school degrees, they only possessed academic knowledge equivalent to an elementary school graduate. The curriculum gradually became more rigourous in later years of the Cultural Revolution, particularly at the high school level after the high schools reopened.

[3]Universities restarted enrollment in 1970-71 after their closure, but the admission was based on recommendations and high school graduates were not eligible to enter universities directly.

[4]Red Guards were a student mass paramilitary social movement mobilized by Mao Zedong in 1966 and 1967, during the Cultural Revolution.

[5]For more evidence on the fact that all birth cohorts ended up having access to high school education, see Appendix A.3.

2.3 The send-down assignment and decisions to stay: Two stages

Two aspects of the movement are central to my identification strategy: (i) The process by which educated urban young people were sent down; (ii) their decisions to stay in the countryside after the end of the movement. Historical documents reveal two criteria of location characteristics used to assign the sent-down youth: rurality and population density. In general, densely populated urban regions lost educated urban youth to sparsely populated rural regions. Section 4 will examine how these two criteria inform resettlement patterns of the sent-down youth.

2.3.1 Send-down process

Despite the send-down criteria, many logistical and administrative constraints prevented the government from assigning exact numbers of sent-down youth to different locations based on the assignment criteria. All these factors resulted in significant diversity in regional human capital shocks, conditional on the assignment criteria.

First, although the send-down decisions were largely centrally planned and implemented, the policy also allowed sent-down youth to choose to relocate to villages where they had close relatives (Liu, 1998, p. 177).

Second, governments at several levels were involved in the administration of the send-down policy. The central government set national guidelines and implemented cross-province relocations. For within-province relocations, provincial governments had some discretion over the planning and implementation of the send-down process. As a result, certain deviations from the send-down criteria across and within provinces occurred. These deviations reflected some provinces' idiosyncratic logistical realities (Bernstein, 1977; Liu, 1998, p. 179-186).

Third, to facilitate implementation of the policy and management of the sent-down youth in the countryside, the government required relative geographic concentration of sent-down youth. A key government document planning the movement stated that the educated urban youth should be "sent down in groups, and should not be too [geographically] dispersed" (China State Council, 1963).

2.3.2 Settlement decisions

With regard to settlement, starting from the end of the Cultural Revolution in 1976, the government began to implement a nationwide policy that allowed most sent-down youth to return to their cities of origin. However, those youth who were married to local residents or employed in nonagricultural jobs in local areas were not allowed to go back (Zhou and Hou, 1999; Xie, Jiang and Greenman, 2008). By the end of the movement in 1979, about 2.86 million people remained in the countryside (Gu, 1996, p. 302-308). Other sources suggest roughly 5% of the total sent-down youth, or 1 million people, permanently settled in the countryside (Li, Rosenzweig and Zhang, 2010). The vast majority of eligible sent-down youth returned to their homes when the movement ended. A main reason for their decision not to settle was that urban residents enjoyed many more advantages relative to rural residents. People living in the countryside had far inferior living conditions than urban residents. The household registration system (*hukou*) that classified the population into "rural" and "urban" residence statuses provided many benefits – such as education, nonagricultural urban jobs, healthcare, and state-owned housing – that were only accessible to urban residents (Liang and White, 1996; Wu and Treiman, 2004).

2.4 External validity

The Down to the Countryside Movement provides a laboratory to study the effects of an exogenous human capital shock on subsequent regional growth. The setting, implementation, and goal of the movement are unique and therefore do not lend themselves to modern policy frameworks. On the other hand, this movement is relevant for several reasons.

First, the movement resulted in a rare, large-scale spatial redistribution of skills within a country. Most other historical episodes of human capital shocks are associated with an influx of foreign immigrants (e.g., Rocha, Ferraz and Soares, 2017). Advanced economies, such as the United States, Canada, or Australia, are able to attract skilled immigrants from other countries. However, most developing countries have to rely on inducing internal migration of high-skilled people to target certain regional growth goals. As a result, my results from the Down to the Countryside Movement are more pertinent to developing countries' regional growth strategies.

Second, my results are also informative for urban-to-rural migration, which is similar in size to rural-to-urban migration (Young, 2013) but has not been the focus of the literature. The literature has mostly focused on rural-to-urban migration (Lucas, 2004). Moreover, my results can also inform place-based policies, many of which target growth of backwards regions.

Third, my results point to the importance of striking a balance of human and physical capital in sustaining economic growth. The literature generally focuses on assessing the importance of human capital versus physical capital in growth (Caballé and Santos, 1993; Funke and Strulik, 2000; Galor and Moav, 2004). However, the send-down movement uniquely featured relocation of high-skilled people to the countryside, with simultaneous retention of physical capital investments in urban areas. This unique feature informs whether human capital shocks alone are able to sustain growth in skill-deficient regions.

Fourth, the movement's resettlement of high-skilled people to previously skill-deficient and rural regions offers a unique lens into the mechanisms of regional economic growth, which has implications for the spatial distribution of economic activities today. As China evolved from an agricultural economy to a hub of manufacturing, the setup of the movement allows me to isolate the causal impact of skill resettlement on structural transformation, agglomeration, and skill structure improvements.

Finally, the Down to the Countryside Movement itself is one of the world's largest skill resettlement programs ever. The movement reshaped the lives of several generations of people in China, and still exerts influences on Chinese society in many fundamental ways.

3 Data and Measurement

My main geographic unit of analysis is prefecture. China has three levels of geographic units that represent partitions of the country – provinces (about 30), prefectures (about 300), and counties (about 3000). I use prefecture as my main geographic unit, as consistent with Au and Henderson (2006). Some prefectures consist solely of county-level urban districts and thus are highly urbanized; however, most prefectures govern large rural areas. Prefecture is a suitable geographic unit in this paper for several reasons: First, the boundaries of prefectures change relatively infrequently compared to those of counties; second, more data are available at the prefecture level; third, as discussed by Davis and Weinstein (2002), the appropriate definition of cities changes over long stretches of time. The last point is particularly relevant for China from 1982 to 2010, as the country underwent massive structural change and urbanization during the period. In certain analyses, when prefecture-level data are unavailable, I use province as my geographic unit of analysis.

3.1 Data sources

I combine data from multiple sources. First, my primary data source is China's six population censuses in 1953, 1964, 1982, 1990, 2000, and 2010. Whenever available, both individual-level sample data and county-level aggregate data are used. Second, I complement data from censuses with information on output, geography, infrastructure, and administrative divisions. Third, I use two province-level data in some analyses: cross-province flows of the sent-down youth; annual provincial investments. I start by discussing my geographic unit of analysis, and then describe the construction of each dataset below. A more complete description of data sources and variables is given in Appendix A.2.

Census data

As the timeline in Figure 1 shows, China has conducted six population censuses since the establishment of the People's Republic of China. Two censuses were conducted before the Down to the Countryside Movement: 1953 and 1964. The other four censuses were conducted after the movement in 1982, 1990, 2000, and 2010. The Census data provide a rich set of economic and demographic information after 1982, including population, migration, educational attainment, and sectoral employment. Population data are available in the 1953 and 1964 censuses; the 1964 census also has data on the number of residents with agricultural registration (*hukou*).

I use individual-level sample of the 1982 Census to construct the skill resettlement rate for each prefecture, which will be discussed in more detail in Section 3.3.

Data on output, geography, infrastructure, and administrative divisions

The 1982 county-level aggregate Census data have information for county output, but such data are not available in later Censuses. I go through every province's statistical yearbook in order to obtain 1990 county output data. The 2000 and 2010 output data are provided by the Institute of Geographic Sciences and Natural Resources Research (IGSNRR) of the Chinese Academy of Sciences.

I use three important sets of additional controls in my regressions. China is a country that has great physical diversity. Thus, geographic characteristics are likely to have been important determinants of regional growth outcomes. My geography control variable is prefecture's average elevation. In addition, I include controls for access to transportation infrastructure. Railroads and highways were closely associated with the mass mobilization of the sent-down youth during the movement, as well as prefectures' access to trade and internal migration since 1982 (Banerjee, Duflo and Qian, 2012). Lastly, I control for administrative dummy variables that indicate whether the prefecture was a special economic zone (SEZ) before 1982 or a provincial capital. SEZs received a tremendous amount of preferential policies; provincial capital is usually a province's center of politics, economy, education, culture, and transportation. As a result, these regions could experience fundamentally different growth rates from other regions, regardless of their skill resettlement rates.

Province-level data

In my analysis, I also use two provincial-level data. First, data on cross-province flows of the sent-down youth measure the numbers of people who were compulsorily relocated across provinces. These data will be compared with my skill resettlement data to check if sent-down youths' settlement decisions were endogenous across provinces.

Second, I obtain annual investment data at the province level. Investment in China is heavily influenced by the government (Chen et al., 2011). As such, capital investments may not always respond to changes in human capital. Any mismatch between human and physical capital can have impacts on productivity growth and thus also population growth. Therefore, I use provincial investments data to study how investments are related to regional variations in skill resettlement before, during, and after the movement.

3.2 Disruption of spatial distribution of high-skilled people

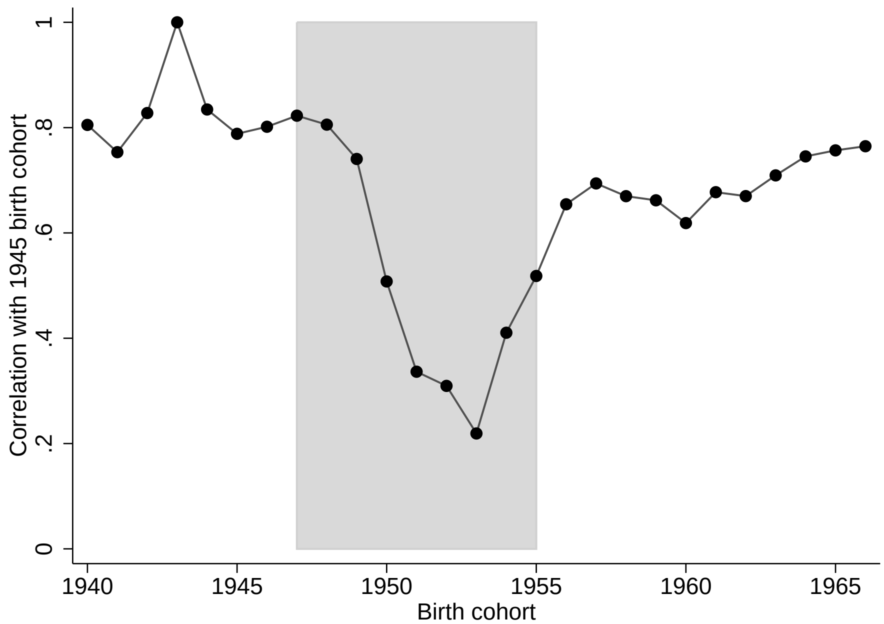
This section looks into the data and shows the spatial distribution of the sent-down youth, in order to corroborate the narratives in Section 2.3. Figure 2 shows the permanent effects of the send-down movement on the the spatial distribution of the skilled people in the impacted cohorts.

I use individual-level data of the 1982 Census sample, which was the first Census conducted after the end of the Movement in 1979. Because almost all sent-down youth who returned to their hometowns went back before 1982, the 1982 Census reflects settlement decisions that the sent-down youth already made. In particular, I collect each individual's age, educational attainment, and prefecture of residence. Based on an evaluation of China's educational system during the Cultural Revolution, as discussed in Section 2.2, I find that high school graduates who were sent down from 1968–73 were the 1947–55 birth cohorts.

For each birth cohort, I can rank all prefectures by their population shares of high-skilled people. This ranking reflects the spatial distribution of high-skilled people for every graduation cohort. I then compute the rank correlation between 1943 birth cohort's distribution and that of every other cohort. The 1943 birth cohort consists of people who graduated right before the start of the movement, and who were thus not sent-down.

Figure 2 plots the correlations. For pre-1947 birth cohorts who were not affected by the send-down movement, the correlations between cohorts stayed high at above 0.8. This suggests that the spatial distribution of high-skilled people was quite stable before the movement. However, for the 1947-55 birth cohorts (shaded area in Figure 2), who were sent down when the send-down policy was rigorously enforced, the spatial distribution between impacted cohorts and the benchmark 1945 unimpacted cohort dropped dramatically. This suggests that the high-skilled people in the sent-down cohorts have substantially different spatial distributions from a cohort that was not affected by the movement even in 1982. The spatial distribution of the high-skilled people was permanently disrupted by the movement.

Figure 2: *Correlations of prefectures' high school graduates shares between 1943 birth cohort and other cohorts, as of 1982*



Notes: The shaded area covers the 1947-55 birth cohorts who were sent down from 1968–73, when the sent-down policy was enforced most rigorously, as discussed in Section 2.3. Data source: 1982 and Census individual-level data 1% samples from IPUMS International.

3.3 Measuring skill resettlement

I define my main policy variable by using the individual-level sample of the 1982 Census. I call the variable "skill resettlement rate", and denote it by $\mathcal{R}_j$ for prefecture j. The key idea of the measurement is to compare, for each prefecture, the differences between two cohorts' proportions of high school graduates, where one cohort was impacted by the Movement, but the other was not. The sign of $\mathcal{R}_j$ indicates whether prefecture j received or lost high-skilled people in the movement. A positive sign represents a receiving region, and a negative sign represents a losing region. The magnitude of $\mathcal{R}_j$ indicates the number of high-skilled people affected by the movement as a portion of total population of their birth cohorts.

Key variables used to construct the measurement are an individual's age, educational attainment, and prefecture of residence in 1982. As discussed earlier, the 1947-55 birth cohorts were impacted by the Movement; in comparison, the cohort that graduated in the preceding years between 1941 and 1946 was not impacted by the Movement.

Let N_j denote total population in prefecture j in 1982. Let $N_{Y,j}$ denote the number of individuals in the send-down cohorts (1947-55 birth cohort) in prefecture j as of 1982. Let $N^H_{Y,j}$ denote the number of individuals in the send-down cohorts in prefecture j who have a high school degree. In comparison, let $N_{U,j}$ denote the number of individuals in the cohorts who graduated before the movement (1941-46 birth cohorts) in prefecture j as of 1982. Let $N^H_{U,j}$ denote the number of individuals in the unimpacted cohorts in prefecture j who have a high school degree.

I define prefecture j's skill resettlement rate as

$$\text{skill resettlement rate}_j \equiv \mathcal{R}_j = \left(N^H_{Y,j} - \frac{N^H_{U,j}}{N_{U,j}} \times N_{Y,j} \right) \Big/ N_j, \tag{1}$$

where the term in the parenthesis is the difference between the actual and estimated numbers of high school graduates in the sent-down cohorts. The estimate of the number of high school graduates in the sent-down cohorts is based on the proportion of high school graduates in the unimpacted cohorts. The skill resettlement rate measures the number of "surprise" high school graduates as a proportion of the prefecture's total population.

3.4 Summary statistics

Table 1 presents summary statistics for initial conditions of China's 295 prefectures. In particular, the skill resettlement rate $\mathcal{R}_j$ ranges from –0.44 at the 10th percentile to 0.63 at the 90th percentile. This suggests that by 1982, several years after the end of the movement, the 10th percentile prefecture lost high-skilled people that amount to 0.44% of its total population. On the other hand, the 90th percentile prefecture received high-skilled people that amount to 0.63% of its total population.

Table 2 presents post-movement characteristics of the sample by census year. From 1982 to 2010, an average prefecture grew its population by about 35%. The productivity growth was remarkable. The average productivity in 2010 was over 25 times the average productivity in 1982. Migrants as share of population grew from 1.13% in 1982 to 12.10% in 2010 on average. This reflects the gradual relaxation of the household registration system *hukou* since 1982, which allowed for big waves

Table 1: *Summary Statistics – Initial Conditions*

	mean	(s.d.)	p10	median	p90
Panel A. Demographic characteristics					
Population density, 1964 (log)	4.74	(1.61)	2.43	5.00	6.22
Skilled share of pop, unimpacted cohort	9.10	(6.75)	3.26	6.65	18.93
Share population nonagr, 1964	22.66	(22.77)	4.98	11.65	61.54
Panel B. Geography, infrastructure					
Average elevation ($\times$100 m)	7.66	(9.23)	0.36	3.54	19.99
Distance to 1962 rail ($\times$10 km)	7.86	(12.47)	0.36	3.06	20.77
Length of 1962 highway/area (km/km^2)	0.03	(0.03)	0.01	0.02	0.04
Panel C. Administrative division					
Special economic zone dummy	0.01	(0.12)	0	0	0
Provincial capital dummy	0.08	(0.28)	0	0	0
Panel D. Skill resettlement					
$\mathcal{R}_j$: skill resettlement rate	0.09	(0.55)	–0.44	0.14	0.63

Notes: This table reports summary statistics for China's 295 prefectures. Tibet's 6 prefectures are not included due to missing data in 1953 and 1964 censuses. See Appendix A.2 for details on data sources and construction.

of internal migration in China. In addition, the agriculture share of employment decreased from 66.49% in 1982 to 48.15% in 2010 on average. On the other hand, service employment took over, and its share increased from a mere 12.80% in 1982 to 29.59% in 2010 on average. Lastly, the educational attainment of the population improved from 1982 to 2010. The illiterate population went down from almost a quarter to less than 5%.

4 Estimation framework

The goal of this paper is to use variation in skill resettlement rates to investigate the effects of human capital shocks on regional growth outcomes, including population growth and productivity growth.

I investigate the relationship between prefecture growth outcomes and skill resettlement rates. My key regression is at the prefecture level:

$$y_j = \alpha + \gamma \mathcal{R}_j + X_j' \delta + \epsilon_j, \tag{2}$$

Table 2: *Summary Statistics – Post-Movement Characteristics*

	1982 mean (s.d.)	1990 mean (s.d.)	2000 mean (s.d.)	2010 mean (s.d.)
Population density (log)	5.19	5.33	5.45	5.54
	(1.56)	(1.57)	(1.61)	(1.63)
Productivity ($\times$1,000 RMB per worker)	1.93	3.45	16.37	48.46
	(2.10)	(2.85)	(19.02)	(33.56)
Share population migrants	1.13	4.56	6.99	12.10
	(1.28)	(5.42)	(8.86)	(12.27)
Share employment...				
Agriculture	66.49	64.41	59.42	48.15
	(24.08)	(25.10)	(24.81)	(24.16)
Manufacturing	20.69	19.99	18.28	22.26
	(17.88)	(17.03)	(14.27)	(13.55)
Services	12.80	15.54	22.30	29.59
	(7.13)	(8.85)	(12.04)	(13.76)
Share population...				
College+	0.78	1.78	4.09	9.20
	(0.93)	(1.93)	(3.49)	(6.09)
High School	7.45	9.43	12.31	14.20
	(4.07)	(5.15)	(5.76)	(5.23)
Middle School	18.47	23.56	32.26	37.05
	(6.53)	(7.09)	(7.73)	(7.56)
Elementary School	33.84	34.55	34.04	27.58
	(6.12)	(7.39)	(8.33)	(8.81)
Illiterate	22.04	16.37	7.91	4.53
	(7.98)	(7.90)	(5.83)	(3.64)

Notes: This table reports summary statistics for China's 295 prefectures. Tibet's 6 prefectures are not included due to missing data in 1953 and 1964 censuses. See Appendix A.2 for details on data sources and construction.

where y_j is some economic outcome, $\mathcal{R}_j$ is the skill resettlement rate, and X_j is a set of control variables. The control variables include log population density in 1964, unimpacted cohort's skilled share, population share with nonagricultural registration, a pretreatment SEZ status dummy variable, a dummy variable for provincial capital, average elevation, distance to the nearest 1962 railroad, and length of 1962 highways per area. The observations are weighted by a generalized continuous-treatment propensity score weighting method, as in Fong, Hazlett and Imai (2017). Appendix B.1 has more detailed discussions about the weighting scheme.

My main regression compares observably identical prefectures that have different skill resettlement rates. In practice, endogenous send-down and settlement decisions could raise selection problems and undermine the comparison of regional growth in prefectures with high and low "skill resettlement rates." Ideally, to estimate the effects of skill resettlement across regions, we would want to (i) randomly assign high-skilled people to different regions independent of regional characteristics (to rule out endogenous send-down location choices) and (ii) eliminate selection biases in the settlement process.

The policy experiment has many features that approximate this ideal setting, whereas it differs from the ideal setting in several other respects. I evaluate the policy experiment and assess the validity of the four key identifying assumptions.

4.1 Send-down process

For the sake of discussion, let's assume for now that the settlement decisions are exogenous across individuals. I will discuss the settlement decisions in Section 4.2. Given this assumption, in terms of the send-down process, the identifying assumption requires that $E(\mathcal{R}_j|\epsilon_j) = 0$ in Equation (2). In other words, the quantity of human capital that was compulsorily relocated needs to be orthogonal to the prefecture's growth prospects.[6]

We first consider this assumption from the individuals' perspective. The send-down decisions were centralized by the national and provincial governments, and individuals had little choice as to whether or where they got sent down. The send-down movement started abruptly and it was therefore an unexpected shock to all people. Moreover, the vast majority of educated urban youth in the impacted cohort were sent down. The send-down policy had few exemptions. During the period of rigorous enforcement from 1968 to 1973, only people who had a severe illness or a disability or were extremely poor were exempted from being sent down. Although there are no national statistics are available that decompose the reasons for not sending down, statistics from representative cities such as Wuhan, shown in Table 3, confirm the stringency of the send-down policy. To the extent that eligibility for exemptions occurred at plausibly similar rates for different regions,

[6] In particular, since $\mathcal{R}_j$ measures the quantity of human capital rather than quality, my identifying assumption does not require the quality of human capital across regions to be orthogonal to prefecture's growth prospects.

we have faith in the assumption that send-down exemptions were random across regions.

Table 3: *Reasons for not sending down, Wuhan*

Year	Percent among graduates	Among which (%)...			
		Sibling	Illness, disability	Extreme poverty	Foreign parents
1969	2.60		65.9	34.1	
1970	3.26		78.9	21.1	
1971	6.81		100.0		
1972	9.95		87.7	12.3	
1973	10.04		100.0		
1974	19.19	27.1	70.5	2.3	0.1
1975	17.72	33.9	51.5	14.5	0.1

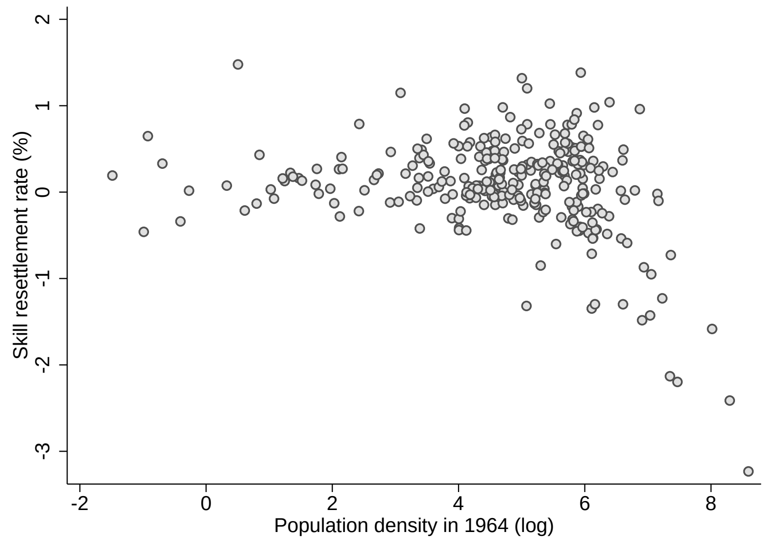
Source: Wuhan Annals of Labor, Appendix Table 23.

On the other hand, from the government's perspective, the send-down assignment across prefectures was not random. As discussed in Section 2.3, government assigned sent-down youth to locations based on two criteria of location characteristics: rurality and population density. Figure 3 shows how skill resettlement rates are associated with location characteristics. The patterns are broadly consistent with the two send-down criteria – the educated urban youth were sent from densely populated urban regions to sparsely populated rural regions. To account for the government's selection on the locations' observable characteristics during the send-down process, conditioning on observable regional characteristics in my estimations is necessary. An implication of the resettlement patterns is that my results are more applicable to scenarios in which high-skilled people migrate from urban to rural areas.

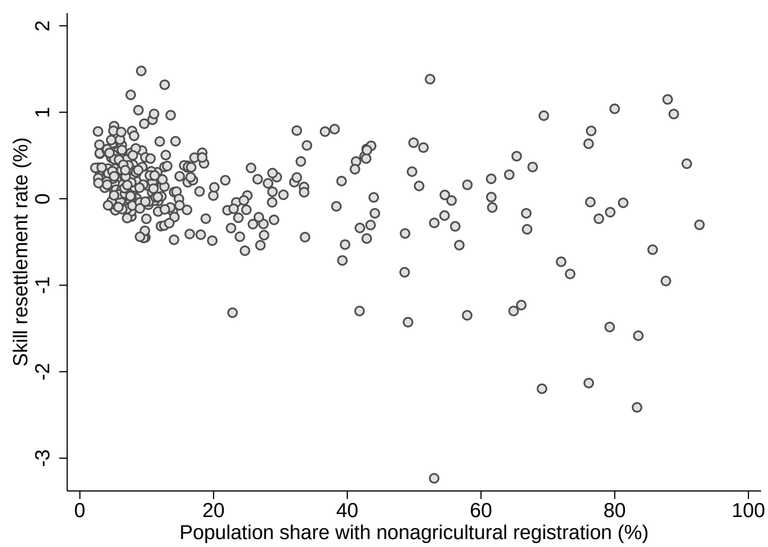
In addition to the identifying assumptions already discussed, an additional assumption is that the government did not select on the locations' *unobservable* characteristics during the send-down process. This identifying assumption would be violated, for example, if the government specifically targeted sending educated urban youth to regions the government believed had better growth potentials, and growth potentials are unobservable from my data.

One way to address concerns about selection on unobservable characteristics is to conduct a placebo pre-trend test in which pretreatment growth is an "outcome" variable. This test is a standard exercise in related papers, such as Kline and Moretti (2013). Although selection on unobservables is fundamentally untestable, if there

Figure 3: *Scatterplot of skill resettlement against selection covariates*



(a) *Population density in 1964*



(b) *Nonagricultural population share*

is no pre-trend, then selections on different unobservables, if they exist, cancel each other out. And if the selections on different unobservables are time-invariant, or if they have the same time-trend, then they don't bias future outcomes. On the other hand, if pre-trend results are big or significant, the possibility of unobserved confounders may lead outcome variables to trend differently in regions receiving different human capital shocks in the decades leading up to the policy intervention.

I have data on population before the 1982 Census years. Table 4 shows falsification tests of the effect of skill resettlement on pre-shock population growth. The regression specification is exactly the same as the main specification as in equation (2). Results are shown in Table 4.

Table 4: *Effects of skill resettlement on pre-shock population growth*

	Population growth 1953–1964
Skill resettlement rate	−4.146
	(4.938)
R^2	0.342

Notes: Standard errors in parentheses clustered at the province level. Growth rates are normalized to decadal growth. Number of prefectures is 292. Regressions weighted by weights calculated as in Fong, Hazlett and Imai (2017). All regressions include the following control variables: log population density in 1964; unimpacted cohort's skilled share; population share with nonagricultural registration; a pretreatment SEZ status dummy variable; a dummy variable for provincial capital; average elevation; distance to the nearest 1962 railroad; length of 1962 highways per area. Statistical significance denoted by * 10%, ** 5%, *** 1%.

The results are not statistically significant, but the negative coefficient does point to the possibility that the government sent educated urban youth down to regions with slow population growth potentials. Such a result is possible if planners intended to use the movement as a means to promote growth of lagging regions. Because of the possibility of government selection on location characteristics that are unobservable in my data, this paper's results need to be interpreted with caution – the results might be lower bounds of the effects of skill resettlement on regional growth in the context of the Down to the Countryside Movement.

4.2 Settlement decisions

I now discuss whether there is potential endogeneity in individuals' settlement decisions after the end of the movement. As I discussed in Section 2.3, the majority of sent-down youth who were eligible to return to cities ended up returning, primarily because of the huge gap between urban and rural life in China at that time. The urban-rural gap is helpful for identification, because it eliminates selection in settlement due to sent-down youths' unobservable assessments of rural regions' heterogeneous growth prospects – most people who were allowed to return to cities would choose to go back.

Two predominant reasons for settlement are marriage and nonagricultural jobs. As of the end of 1979, 15% of the total number of sent-down youth that remained in the countryside were married. This accounted for a relative minority of the stayers. In addition, to some extent we believe that marriage to local residents may be plausibly random across prefectures.

In addition to marriage, sent-down youth who were already assigned nonagricultural jobs were not allowed to move back. Even if marriage is random across regions, we should still be concerned that regions might have different retention rates of high-skilled people due to jobs. Different retention rates may arise because different regions might experience different increases in the nonagricultural sectors during the program period. To address this concern, I proxy availability of jobs for the sent-down youth using changes in the region's share of the nonagricultural sector from 1964 to 1982. I then regress the skill resettlement rate on the job availability proxy, conditional on the forced-relocation rate. The goal is to check whether job availability is associated with differences in skill settlement rates. Results are shown in column (1) of Table 5.

Table 5: *Relationship between resettlement rates and job availability, forced-relocation rates*

	(1)	(2)
Job availability proxy	−0.088	
	(0.106)	
Forced relocation rate	2.356***	2.344***
	(0.472)	(0.459)
R^2	0.621	0.613

Notes: Dependent variable is the skill resettlement rate. Regression on 29 provinces. Robust standard errors in parentheses. Statistical significance denoted by *** 1%.

The results indicate that variations in job availability have little and statistically insignificant association with variations in skill resettlement rates, conditional on the forced-relocation rates. In addition, column (2) of Table 3 runs the bivariate regression of skill resettlement rates on forced relocation rates. By comparing the two columns of the table, we see that job availability does not account for any additional variation in skill resettlement rates across space.

5 The effects of skill resettlement on regional growth

5.1 Effects on population growth

I start by examining the effects of skill resettlements on regional population growth. Table 6 reports the results from estimating equation (2) using population growth rates from 1982-1990 (panel A), 1982-2000 (panel B), and 1982-2010 (panel C) as dependent variables. The growths are measured from 1982 onward, and 1982 was already a few years after the end of the movement. Thus the results I obtain are not mechanical population growth due to population redistribution across regions from the movement. Moreover, the growth rates in Table 6 are all normalized to decadal growth, so the results can be compared across different time horizons.

Column 1 of Table 6 reports my baseline results. In columns 2 and 3, I drop controls for geographic characteristics and infrastructure, respectively. The point estimates on the skill resettlement rate variable in columns 2 and 3 are very similar to the baseline point estimate. On the other hand, the confidence interval for the baseline result is tighter than results in columns 2 and 3. This suggests that our results are robust to controlling for geographic and initial infrastructure differences across prefectures, but geographic and infrastructure characteristics do help explain variations in population growth subsequent to the movement.

Column 4 drops the set of controls for administrative indicators. The results in column 4 are very different from the baseline result in column 1. In particular, the point estimates become much smaller than the baseline result. Recall that the administrative indicators include an indicator for the pre-1982 special economic zone (SEZ) designation and an indicator for provincial capital. SEZs and provincial capitals are regions that received a significant amount of resources and that also benefited from preferential policies. Provincial capitals were also regions that lost a large number of educated young people during the send-down movement. The difference between results in column 4 and the baseline suggests that SEZs and provincial capitals grew very fast after the end of the movement, despite losing many high-skill young people. The difference also suggests that the send-down movement has heterogeneous effects across regions. I will discuss heterogeneous effects in more detail in Section 5.3.

Table 6: *Effects of skill resettlement on regional population growth*

	(1)	(2)	(3)	(4)
Panel A. 1982-1990				
Skill resettlement rate	8.727***	7.765**	8.579***	6.171
	(2.886)	(2.932)	(3.007)	(4.092)
R^2	0.450	0.448	0.448	0.083
Panel B. 1982-2000				
Skill resettlement rate	5.966***	4.958**	5.790**	4.257**
	(2.070)	(2.123)	(2.121)	(1.894)
R^2	0.499	0.495	0.497	0.125
Panel C. 1982-2010				
Skill resettlement rate	2.699	1.770	2.513	1.844
	(1.969)	(1.900)	(2.060)	(1.616)
R^2	0.541	0.533	0.537	0.219
Number of prefectures	295	295	295	295
Selection covariates	Yes	Yes	Yes	Yes
Geography	Yes	No	Yes	Yes
Infrastructure	Yes	Yes	No	Yes
Administrative indicators	Yes	Yes	Yes	No

Notes: Robust errors in parentheses, clustered at the province level. Growth rates are normalized to decadal growth. Regressions weighted by weights calculated as in Fong, Hazlett and Imai (2017). Selection covariates are log population density in 1964, unimpacted cohort's skilled share, and population share with nonagricultural registration in 1964. Geographic characteristics include prefecture's average elevation. Infrastructure characteristics are distance to the nearest 1962 rail, and total length of 1962 highway within prefecture. Administrative indicators include an indicator for pre-1982 special economic zone (SEZ) designation, and an indicator for provincial capitals. Statistical significance denoted by * 10%, ** 5%, *** 1%.

5.2 Effects on productivity growth

I next investigate how skill resettlement affects regional productivity growth. Table 7 reports the results from estimating equation (2) using productivity growth rates from 1982-1990 (panel A), 1982-2000 (panel B), and 1982-2010 (panel C) as dependent variables. Productivity is measured as output per worker.

The results indicate that skill resettlement has no statistically significant effect on productivity growth, across all specifications which include different sets of control variables. In terms of the point estimates, my baseline estimates shown in column 1 of Table 7 suggest that skill resettlement has positive effect on productivity growth in the first decade from 1982-1990, but the effect turned negative over longer time horizons. Dropping infrastructure (column 3) or administrative

Table 7: *Effects of skill resettlement on regional productivity growth*

	(1)	(2)	(3)	(4)
Panel A. 1982-1990				
Skill resettlement rate	−3.243	−2.615	−3.325	−6.027
	(46.184)	(46.439)	(49.328)	(44.764)
R^2	0.193	0.193	0.183	0.149
Panel B. 1982-2000				
Skill resettlement rate	−3.353	7.563	−5.232	−2.726
	(18.508)	(17.411)	(18.428)	(20.225)
R^2	0.117	0.074	0.104	0.099
Panel C. 1982-2010				
Skill resettlement rate	−18.521	−10.745	−17.874	−18.390
	(13.025)	(13.386)	(12.021)	(12.768)
R^2	0.298	0.260	0.280	0.293
Number of prefectures	295	295	295	295
Selection covariates	Yes	Yes	Yes	Yes
Geography	Yes	No	Yes	Yes
Infrastructure	Yes	Yes	No	Yes
Administrative indicators	Yes	Yes	Yes	No

Notes: Robust errors in parentheses, clustered at the province level. Growth rates are normalized to decadal growth. Regressions weighted by weights calculated as in Fong, Hazlett and Imai (2017). Selection covariates are log population density in 1964, unimpacted cohort's skilled share, and population share with nonagricultural registration in 1964. Geographic characteristics include prefecture's average elevation. Infrastructure characteristics are distance to the nearest 1962 rail, and total length of 1962 highway within prefecture. Administrative indicators include an indicator for pre-1982 special economic zone (SEZ) designation, and an indicator for provincial capitals. Statistical significance denoted by * 10%, ** 5%, *** 1%.

indicators (column 4) controls do change the point estimates much.

On the other hand, the point estimates are different from the baseline results if we drop the geography control, as shown in column 2 of Table 7. Recall that my control for geographic characteristic is the prefecture's average elevation. The difference between column 2 and column 1 suggests that skill resettlement may have positive (although insignificant) effect on productivity growth conditioning on all control variables other than the geographic characteristic, but the positive effect may be attributed to the fact that we are comparing prefectures with different elevations. If we condition on elevation, the point estimates will turn negative. Again, the difference in results between column 2 and the baseline suggests that skill resettlement may have heterogenous effects across regions.

5.3 Heterogeneous effects across regions

Does the effect of skill resettlement vary across regions with different exposures to the human capital shock? In order to evaluate heterogenous effects of skill resettlement, I split the sample where the cutoff is the median of $\mathcal{R}_j$ at around -0.16. This creates a subsample of receiving regions with positive human capital shocks and another subsample of losing regions with negative human capital shocks. Results are robust with different cutoff values, albeit with different magnitudes.

Table 8: *Heterogeneous effects of skill resettlement*

	Receiving regions		Losing regions	
	Pop Growth (1)	Prod Growth (2)	Pop Growth (3)	Prod Growth (4)
Panel A. 1982-1990				
Skill resettlement rate	2.982	158.166**	46.886*	−73.833*
	(3.092)	(67.481)	(26.261)	(38.017)
R^2	0.255	0.264	0.651	0.257
Panel B. 1982-2000				
Skill resettlement rate	5.769*	54.133*	26.009	−7.806
	(2.859)	(31.366)	(17.774)	(24.321)
R^2	0.342	0.392	0.691	0.074
Panel C. 1982-2010				
Skill resettlement rate	5.808**	26.818	10.895	−33.878
	(2.194)	(27.652)	(9.624)	(21.955)
R^2	0.408	0.425	0.724	0.286
Number of prefectures	150	150	145	145

Notes: Robust errors in parentheses, clustered at the province level. Growth rates are normalized to decadal growth. Regressions weighted by weights calculated as in Fong, Hazlett and Imai (2017). Selection covariates are log population density in 1964, unimpacted cohort's skilled share, and population share with nonagricultural registration in 1964. Geographic characteristics include prefecture's average elevation. Infrastructure characteristics are distance to the nearest 1962 rail, and total length of 1962 highway within prefecture. Administrative indicators include an indicator for pre-1982 special economic zone (SEZ) designation, and an indicator for provincial capitals. Statistical significance denoted by * 10%, ** 5%, *** 1%.

Table 8 reports results for both the receiving and losing regions. The results come from estimating equation (2) with all control variables. Columns 1 and 3 of Table 8 use population growth as the dependent variable; columns 2 and 4 use productivity growth as the dependent variable. The inclusion of all control variables makes results in Table 8 comparable to the baseline results in Sections

5.1 and 5.2, reported in column 1 of Tables 6 and 7. The results suggest that skill resettlement has positive effects on both population and productivity growths in the receiving regions. The receiving regions are predominately rural, less educated, and sparsely populated areas. On the other hand, skill settlement has negative effects on productivity growths in the losing regions, which tend to be more urbanized, better educated, and densely populated.

Explanations for heterogenous effects

Why would skill resettlement have drastically different effects on receiving and losing regions? To answer this question, I turn to an investigation of the reasons for heterogeneity. A key observation is that the receiving and losing regions are fundamentally different places: The losing regions are more developed than the receiving regions. In terms of location fundamentals, the losing regions have comparative advantage in accommodating and utilizing human capital over the receiving regions. The send-down movement created a deliberate mismatch in the spatial distribution of human capital.

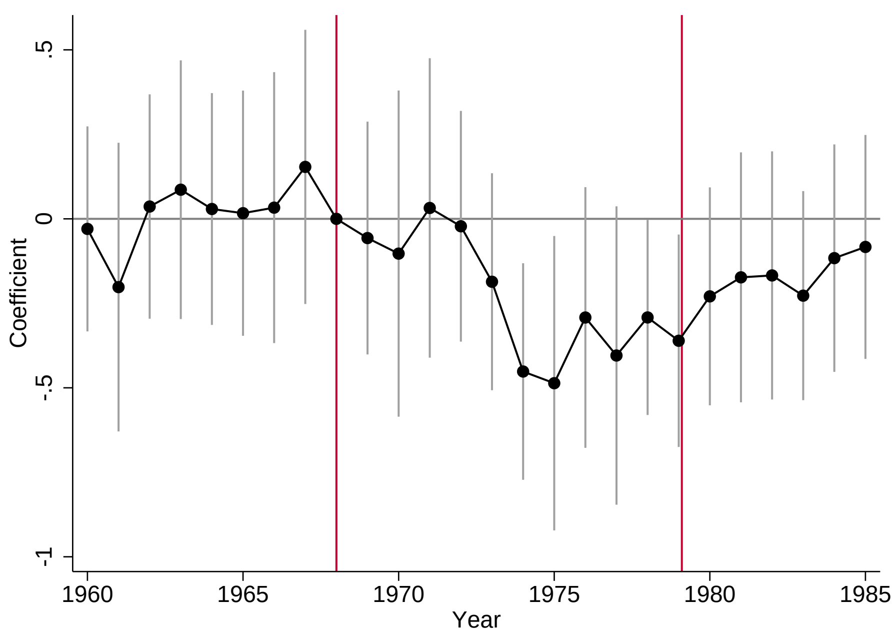
The above observation, however, does not rationalize the negative coefficient estimates for losing regions. Why would a region that lost more high-skilled people grew faster than another observably identical region that lost fewer high-skilled people? To understand these negative coefficients, recall from Section 2 that the objective of the movement was not to invest in rural areas. As a result, it is probably that investments did not the send-down youth to rural areas as a consequence of the movement. The fact that investments were centralized in China makes this scenario even more likely. I turn to a formal test to check whether is indeed the case.

Using annual investments data at the province level from 1960 to 1985, I compute each province's shares of national total investments in every year. Based on the dataset, I specify a difference-in-differences regression to estimate the relationship between skill resettlement and provincial investment shares through years leading up to and after the movement. The difference-in-differences specification features continuous treatment (different skill resettlement rates for different provinces) and multiple time periods. Identical counterfactual trends across provinces remains the standard identifying assumption. Let k be the time at which the treatment is being switched. The difference-in-differences model is

$$y_{pt} = \gamma_p + \lambda_t + \sum_{\substack{j=-m \\ j\neq 0}}^{s} \beta_j D_{jt}(t = k + j) + \epsilon_{pt} \tag{3}$$

I run the difference-in-differences regression as specified by (3) on the panel data, where the outcome variable is yearly investment share of the provinces. On the right hand side, I include year fixed effect (λ_t) and province fixed effect (γ_p), and a set of skill resettlement rates interacted with the year dummies with 1968 as the base year ($D_{jt}(t = k + j)$). Using 1968 as base year indicates that the send-down program was "switched on" in 1968. In this specification, instead of a single treatment effect, we have now also included m "leads" and s "lags" of the treatment effect. β_j is the coefficient on the jth lead of lag. A test of the difference-in-differences assumption is $\beta_j = 0 \forall j < 0$, i.e., the coefficients on all leads of the treatment should be zero. Such a specification is similar to the one in Autor (2003).

Figure 4: *Coefficient estimates of* β_j



Notes: The estimation is based on Equation (3). The baseline year is 1968. For all other years, the grey bars represent the 95% confidence interval of the coefficient estimates.

Figure 4 plots the coefficients β_j on the skill resettlement rates interacted with the year dummies. Year 1968 is the base year and its coefficient is normalized to zero.Before the movement, skill resettlement has no relationship with changes in provinces' investment shares, as expected for the pre-trend. As the movement started, if capital investments followed with human capital that was sent-down to the countryside, we would expect the coefficients to turn positive as a consequence of the movement. On the other hand, the coefficients stayed at around zero in the first few years of the movement, and turned negative afterwards. In other words, provinces with *higher* skill resettlement rates experienced unusually *lower* shares of investments during the Movement period. As a result, while high-skilled people were sent down, capital investments continued to concentrate, or became even more concentrated, in initially more developed areas. This result is related to the capital deepening literature (Acemoglu and Guerrieri, 2008).

In summary, the reasons for the heterogenous effects of skill resettlement are three-fold. First, location fundamentals determined that losing regions that are more accommodative to human capital were not adversely impacted by their loss of high-skilled young people. Second, because the movement was driven by ideology rather than a development program, centralized capital investments did not follow the path of human capital. In fact, places that lost more educated young people appeared to receive a higher share of national investments as a consequence of the movement. As a result, skill resettlement has negative though insignificant effects on the losing regions. Third, when we focus on the receiving regions, skill resettlement has positive effects, likely due to agglomeration economies as we will discuss further in Section 6.

6 Channels of regional growth

6.1 Agglomeration

Section 5 discusses the effects of skill resettlement on regional population and productivity growth. I next document how this initial human capital shock persisted through time. First, I investigate the source of population growth. Typically, population growth can be driven by either migration or fertility. If we believe in knowledge spillovers due to presence of high-skilled people, we should expect prefectures with higher skill resettlement rates to attract more migrants (Simon and Nardinelli, 2002, Davis and Dingel, 2012). In the context of this paper, a migrant is defined as a person who lives outside of the prefecture of his or her registration. In other words, a migrant does not have *hukou* in the prefecture of residence.

To disentangle the two sources of population growth, I first calculate the percentage point increases in population and migration, respectively, as shares of 1982 prefecture population. Then I decadalize the percentage point increases. This formulation will allow me to uncover the proportion of population growth that can be attributed to attracting migration. Columns 1 and 2 of Table 9 show the results where the I regress the decadalized percentage point increases in population and migration on the skill resettlement rate and my baseline controls.[7] Column 3 computes the share of population growth that is attributable to migration by dividing point estimates in column 2 by point estimates in column 1. The results in column 2 suggest that migration is the main driver of skill resettlement-induced regional population growth. In the first decade, almost two thirds of the faster population growth can be attributed to migration. Over longer time horizons, migration became even more important, accounting for over 90% of the faster population growth in regions with higher skill resettlement rates.

Not only does migration account for a large proportion of the faster population growth, the effect of skill resettlement on migration is also substantial. Recall from Table 1 that the skill resettlement rate has a standard deviation of 5.14. Thus, based on the estimate from Panel C of column 2 (which is decadalized), we see that a one standard deviation increase in skill resettlement rate would leave to almost a 20 percentage point increase in migration as share of prefecture's 1982 population.

[7] Table 6's baseline estimate and Table 9 are different because growths are defined differently. The control variables are the same. In Table 6, growth is measured as the grow rate. In Table 9, growth is measured as the percentage increase. There are a few reasons for using different measures of growth: (1) "Growth rate" is a more appropriate measure of growth, because the "percentage increase" measure also blends in the compounding effect (the compounding effect becomes apparent when comparing Tables 6 and 9). Due to compounding, '82-'90 percentage increase is not exactly comparable to '82-'00 percentage increase, even after decadal normalization. As a result, I use the conventional "growth rate" approach in Table 6. (2) On the other hand, simple decomposition is not feasible with "growth rates". Hence I use "percentage increases" in Table 9. (3) As a side note, I didn't use the difference in log of populations when calculating growth rates, because some growth rates are huge, particularly for the 1982-2010 productivity growth. As a result, the log approximation will deviate a lot from the actual growth rates.

Table 9: *Channels of regional growth: Migration*

	Population (1)	Migration (2)	% Migrants (3)
Panel A. 1982-1990			
Skill resettlement rate	7.636***	3.653*	47.84
	(2.478)	(1.884)	
R^2	0.452	0.464	
Panel B. 1982-2000			
Skill resettlement rate	11.050**	7.535	68.19
	(4.778)	(5.177)	
R^2	0.467	0.457	
Panel C. 1982-2010			
Skill resettlement rate	8.548	4.005	46.85
	(5.243)	(5.288)	
R^2	0.482	0.463	
Number of prefectures	295	295	

Notes: Robust errors in parentheses, clustered at the province level. The dependent variables in columns 1 and 2 are percentage points increases in population and migration, respectively, as shares of 1982 prefecture population. The percentage point increases are normalized to decadal increases. Regressions weighted by weights calculated as in Fong, Hazlett and Imai (2017). Selection covariates are log population density in 1964, unimpacted cohort's skilled share, and population share with nonagricultural registration in 1964. Geographic characteristics include prefecture's average elevation. Infrastructure characteristics are distance to the nearest 1962 rail, and total length of 1962 highway within prefecture. Administrative indicators include an indicator for pre-1982 special economic zone (SEZ) designation, and an indicator for provincial capitals. Statistical significance denoted by * 10%, ** 5%, *** 1%.

This is substantial, since Table 2 documents that an average prefecture only saw a population growth of about 35% over the entire period from 1982 to 2010.

6.2 Skill composition

I next provide evidence on how skill resettlement changes the skill composition in a region. Similar to the previous subsection, I calculate decadalized percentage point increases in population by skill levels, as shares of 1982 prefecture population. Table 10 shows the results where I regress the decadalized percentage point increases in population by skill levels on skill resettlement rate and controls. The dependent variables in columns 2, 4 and 6 are the increases in population belonging to each educational category divided by the 1982 total population. For expositional clarify, here I only use three skill levels. High skill consists of college and high school graduates; middle skill consists of middle school graduates; low skill consists of elementary school graduates and illiterate people.

Columns 3, 5 and 7 of Table 10 show the relative contributions each skill level to the faster population growth. Note that these numbers do not add up to 100 because children under 6 are excluded from the educational attainment reporting, so the difference from 100 represents the relative contribution of growth in the number of children.

Table 10: *Channels of regional growth: Skill levels*

	High Skill (2)	% High (3)	Middle Skill (4)	% Middle (5)	Low Skill (6)	% Low (7)
Panel A. 1982-1990						
Skill resettlement rate	0.361	6.64	2.968**	54.60	2.107	38.76
	(0.788)		(1.273)		(1.418)	
R^2	0.564		0.449		0.390	
Panel B. 1982-2000						
Skill resettlement rate	2.368	21.81	6.475**	59.63	2.016**	18.57
	(1.595)		(2.371)		(0.904)	
R^2	0.501		0.433		0.476	
Panel C. 1982-2010						
Skill resettlement rate	2.582	30.88	4.947**	59.17	0.562	6.72
	(2.121)		(2.175)		(0.973)	
R^2	0.513		0.431		0.541	
Number of prefectures	295		295		295	

Notes: Standard errors in parentheses clustered at the province level. The dependent variables in columns 1, 2, 4 and 6 are percentage points increases in total population and population by skill levels, as shares of 1982 prefecture population. High skill consists of college and high school graduates; middle skill consists of middle school graduates; low skill consists of elementary school graduates and illiterate people. The percentage point increases are normalized to decadal increases. Regressions weighted by weights calculated as in Fong, Hazlett and Imai (2017). All regressions include the following control variables: log population density in 1964; unimpacted cohort's share of high skills; population share with nonagricultural registration; a pretreatment SEZ status dummy variable; a dummy variable for provincial capital; average elevation; distance to the nearest 1962 railroad; length of 1962 highways per area. Statistical significance denoted by * 10%, ** 5%, *** 1%.

A key takeaway from Table 10 is that population with all skill levels grew. Recall from Table 2 that high, middle, and low skill shares of population were 11.21, 23.56, and 50.92, respectively, in 1990; and 23.40, 37.05, and 32.11, respectively, in 2010. Therefore, the low-skilled population growth always contributed less to total population growth relative to its share. Middle-skilled population growth always contributed more to total population growth relative to its shares. High-skilled population growth made a contribution in the first decade, but started to make large contributions from the second decade. In summary, skill resettlement induced more growth in the mid- to high-skilled population.

To understand the negative growth of the high-skilled population in the first decade, notice that the population growth by skills here commingled two different effects: net in-migration of people with certain skills, and people from the prefecture getting better educated. The negative growth of the high-skilled population in the first decade is likely due to more outflows of high-skilled people from regions with higher skill resettlement rates. Regions with higher skill resettlement rates had more compulsorily relocated people, who were more likely to leave those regions. Over time, however, the pattern of geographic skill sorting started to emerge, a phenomenon that has been documented in other countries (Davis and Dingel, 2014; Diamond, 2016).

6.3 Structural transformation

I next provide evidence that skill resettlement induced a structural transformation in economic activity. Davis and Haltiwanger (1999) has documented that allocative and aggregate shocks have impacts on employment fluctuations and job reallocations. Davis and Haltiwanger (2001) finds that oil shocks trigger considerable job reallocation.

In my paper, the long-term growth in productivity in positive skill resettlement regions, as documented in Section 5.3, is likely to have been a consequence of the improved skill structure. In Table 11, I assess specifically how improved regional skill structure translated into higher productivity in the long run. More specifically, I analyze whether the presence of more high-skilled people allowed individuals to engage in more skill-intensive economic activity.

Similar to the previous subsection, I calculate decadalized percentage point increases in total and sectoral employment, as shares of 1982 prefecture population. Table 11 shows the results where I regress the decadalized percentage point increases in employment on skill resettlement rate and controls. The results indicate that skill resettlement has positive effects on employment. In addition,

Table 11: *Channels of regional growth: Total and sectoral employment*

	Employment (1)	Agriculture (2)	% Agriculture (3)	Manufacturing (4)	% Manufacturing (5)	Services (6)	% Services (7)
Panel A. 1982-1990							
Skill resettlement rate	5.918	1.678	28.35	2.635	44.53	1.605	27.12
	(3.890)	(4.037)		(2.575)		(1.440)	
R^2	0.426	0.295		0.448		0.516	
Panel B. 1982-2000							
Skill resettlement rate	13.208*	4.240	32.10	6.904	52.27	2.064	15.63
	(7.209)	(3.814)		(6.817)		(2.838)	
R^2	0.446	0.368		0.442		0.480	
Panel C. 1982-2010							
Skill resettlement rate	9.994	3.965	39.67	3.190	31.92	2.839	28.41
	(8.114)	(2.450)		(5.947)		(3.762)	
R^2	0.461	0.434		0.456		0.483	
Number of prefectures	295	295		295		295	

Notes: Standard errors in parentheses clustered at the province level. The dependent variables in columns 1, 2, 4 and 6 are percentage points increases in total employment and employment by sectors, as shares of 1982 prefecture population. The percentage point increases are normalized to decadal increases. Regressions weighted by weights calculated as in Fong, Hazlett and Imai (2017). All regressions include the following control variables: log population density in 1964; unimpacted cohort's skilled share; population share with nonagricultural registration; a pretreatment SEZ status dummy variable; a dummy variable for provincial capital; average elevation; distance to the nearest 1962 railroad; length of 1962 highways per area. Statistical significance denoted by * 10%, ** 5%, *** 1%.

while all three sectors experienced growth to some extent, the main driver is the manufacturing sector. Starting from 1982, China transitioned from a heavily agricultural economy to a more manufacturing oriented economy, and those prefectures that received more skill settlement shocks appear to have a leg up on the others.

7 Conclusion

This paper uses plausibly exogenous variation from a large-scale skill resettlement program in China to identify the determinants and mechanisms of regional growth. I show that in contrast to many papers in the literature, human capital shocks only had positive effects on regional population growth in the short run, and had negligible effects on productivity growth.

Two features of the program turn out important for rationalizing these results. The mismatch between human capital and location fundamentals allows me to investigate the heterogenous effects of human capital shocks across regions with different characteristics. I show that location fundamentals matter in determining regional growth. In addition, whereas high-skilled people were sent-down during the Movement, physical capital investments did not follow as investment decisions were centralized in China. In regions where high-skilled people were sent-down, the lack of complementary physical capital input was another deterrence of regional productivity growth. As a result, human capital alone is not able to induce sustained regional growth.

My findings shed new light on the determinants of regional growth, in particular the relationship between human capital and other factors of growth such as location fundamentals and physical capital. My policy experiment suggests that human capital is indeed an important determinant of regional growth, but location fundamentals and physical capital investments also play major roles.

I further identify key mechanisms of regional growth. Structural transformation from the agricultural sector to the manufacturing sector induced by the human capital shocks drives regional growth. Migration, rather than fertility, is another driving force of population growth following the human capital shocks. However, I find that agglomeration is localized within provinces. Lastly, human capital shocks affect regional growth through further skill composition improvement.

My results also have important implications for the establishment of future place-based policies. Because many place-based policies aim to promote growth of regions with worse location fundamentals, a good policy design should ensure that both human capital and physical capital are induced to relocate to the target regions. Otherwise, the place-based policy's effects will diminish over time.

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Appendices

A Appendix: Data

A.1 Defining high skills

In order to carry out the analysis, I need to define high skill in the context of China. I use observed educational attainment as a proxy for individuals' skills, following a large literature. Although educational attainment is a coarse measure, it is the most consistent and reliable measure available in data describing a large number of people over an extended time period across granular geographic locations.

Table A.1 shows China's prime-age (ages 25-54) population shares by educational attainments from 1982 to 2010. China has made great strides in eliminating illiteracy over the three decades, but the proportion of its population that has attained high school or college level education has remained relatively small. Even in 2010, only about 27.2% of its population had received high school or college education; whereas in 1982, the high school or college educated population only accounted for 8.2% of the total prime-age population.

Table A.1: *China: Prime-age population shares by educational attainments, 1982–2010*

Education	1982	1990	2000	2010
College+	.012	.024	.049	.110
High school	.070	.135	.143	.162
Middle school	.199	.295	.428	.511
Elementary school	.371	.368	.327	.197
Illiterate	.347	.178	.054	.019

Notes: Prime age consists of ages from 25 to 54. Data sources: 1982 and 1990 Census individual-level data 1% samples from IPUMS International; Tabulations on the 2000 and 2010 Census from the National Bureau of Statistics of China.

For the purpose of this study, because the send-down movement only affected secondary school graduates, I define high-skilled individuals in China as those that graduated from high schools. Although it is different from traditional urban economics literature that defines high-skilled in developed countries as college graduates, this definition is consistent with the Chinese facts presented in Table A.1.

A.2 Data sources

Data used in this paper come from the following sources:

1. *China censuses in 1953, 1964, 1982, 1990, 2000, 2010*. These include all population censuses conducted in China after the establishment of the People's Republic of China. I use county-level aggregate data from all Census years. All county-aggregate datasets include information on population. The availability of other information varies by census. Data on employment by sectors are available after 1982. Data on migrants and population by educational attainments are available after 1990. The 1964 dataset has each county's population with nonagricultural registration (*hukou*). The 1982 dataset has information on output (gross value of agricultural and industrial output). I also use 1982 Census individual-level 1% sample data to obtain data on migration, population by educational attainment in 1982; and to construct variables related to skill resettlement.

2. *GIS maps of China's administrative boundaries*. The GIS maps include boundaries of county-level jurisdictions in each year the Census was conducted. I also calculate the area of counties, and define prefectures with consistent boundaries based on the GIS maps.

3. *Provincial statistical yearbooks*. I go through all provinces' statistical yearbooks to obtain county-level output data for 1990.

4. *Socioeconomic data from IGSNRR, Chinese Academy of Sciences*. In particular, I compute prefecture GDP data in 2000 and 2010 based on IGSNRR's socioeconomic data.

5. *Geographic data from IGSNRR, Chinese Academy of Sciences*. These include: (i) high resolution images of land use patterns covering the entire geography of China in 1980, 1990, 2000, and 2010; (ii) Digital Elevation Model (DEM) data which is overlaid with GIS maps to calculate a prefecture's average elevation.

6. *NOAA DMSP-OLS night lights data*. I download night lights data for 1992 (the first year digitized night lights data become available), 2000, and 2010, and overlay the data with Chinese GIS maps.

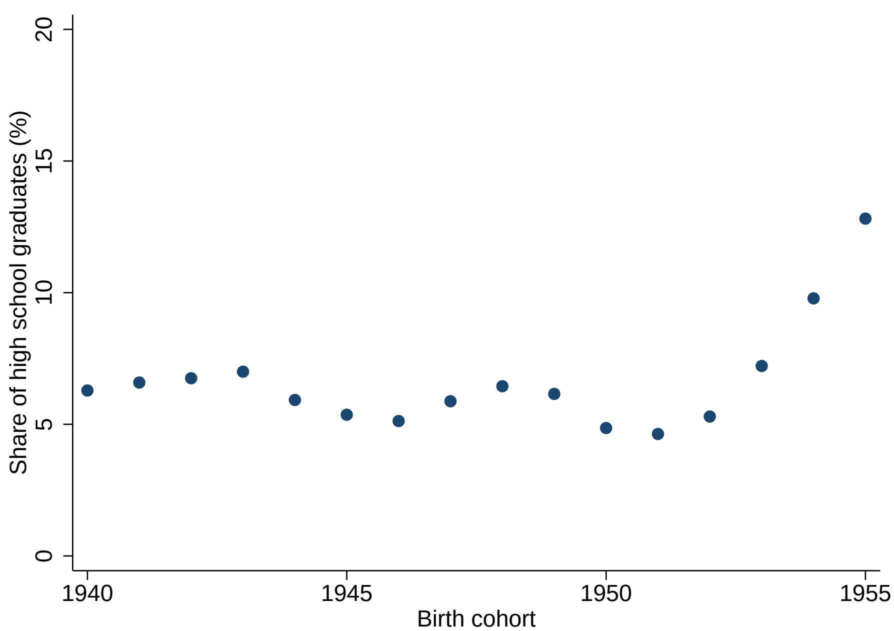
7. *GIS maps for roads, railroads, and highways in 1962*. This dataset is collected by Baum-Snow et al. (2017) and is generously provided by the University of Toronto library.

8. *China Compendium of Statistics*. This dataset includes annual province-level investment data.

A.3 All birth cohorts had access to high school education

Figure A.1 plots the shares of high school graduates for 1940-1955 birth cohorts. The key message of this figure is to show that all birth cohorts had access to high school education, despite school closure from 1966 to 1967. For more institutional details, see Section 2.2.

Figure A.1: *Share of high school graduates by birth cohorts*



Data source: 1982 and Census individual-level data 1% samples from IPUMS International.

B Appendix: Empirical strategy

B.1 A continuous-treatment weighting method

In this section, I discuss my continuous-treatment weighting method proposed by Fong, Hazlett and Imai (2017). This method is a generalization of the conventional binary-treatment propensity score weighting method. I first provide a simplified version of mathematical details, and then discuss features and benefits of using this weighting method.

Brief overview of methodology

Before I discuss Fong, Hazlett and Imai (2017)'s method, let's recall how the binary-treatment propensity score weights are computed. Let Z be a binary indicator variable denoting whether treatment is received. The first step is to calculate the propensity score, which Rosenbaum and Rubin (1983) define in their seminal paper as the probability of treatment assignment conditional on observed baseline covariates X_i:

$$e_i = \Pr(Z_i = 1|X_i). \tag{4}$$

The propensity score is a balancing score: conditional on the propensity score, the distribution of measured baseline covariates is similar between treated and untreated groups. The binary-treatment weighting method, namely the inverse probability of treatment weighting (IPTW), generates weights based on the propensity score to create a synthetic sample in which the distribution of measured baseline covariates is independent of treatment assignment. Specifically, weights are defined as

$$w_i = \frac{Z_i}{e_i} + \frac{1 - Z_i}{1 - e_i}. \tag{5}$$

Notice that equation (5) is equivalent to $w_i = 1/\Pr(Z_i = 1|X_i)$ for the treated group, and $w_i = 1/\left(1 - \Pr(Z_i = 1|X_i)\right)$ for the untreated group. In other words, we construct the IPTWs by estimating each person's probability of their respective treatment status, based on the observed covariates, and then weight by the inverse of the estimated probability.

The Fong, Hazlett and Imai (2017) method is essentially a generalization of IPTW and is applicable to continuous-treatment cases. In its simplest form, let T_i be a continuous-treatment for observation i, and let X_i be observed covariates. Then the weight is given by

$$w_i = \frac{f(T_i)}{f(T_i|X_i)}, \tag{6}$$

where $f(\cdot)$ is the probability density function. For more details about this weighting method, please refer to Fong, Hazlett and Imai (2017).

Related research

The propensity score weighting method, in its various forms, has been widely used in empirical studies. For instance, in an influential recent paper that evaluates the Tennessee Valley Authority, Kline and Moretti (2013) run the Oaxaca-Blinder regression, which Kline (2011) argues is a propensity score reweighting estimator. Another well-known application of the binary-treatment propensity score weighting method is Sianesi (2004), who evaluates a Swedish active labor market program in the 1990s. In that paper, Sianesi (2004) points out that although the validity of matching still relies on assuming away selection on unobservables as in OLS, it can eliminate two sources of bias: (i) the bias due to the difference in the supports of observable covariates in the treated and untreated groups, and (ii) the bias due to the difference between the two groups in the distribution of observable covariates over its common support. Point (ii) is also highlighted in Kline and Moretti (2013), who argue that their regression method identifies the average treatment effects on the treated group in the presence of treatment heterogeneity.

In addition to identifying the average treatment effects in the presence of treatment heterogeneity, weighting may also increase the precision of the point estimate. After applying the weights, the correlation between the treatment variable and the selection covariates will be minimized; including the selection covariates in the weighted regression will thus lower the standard error of the point estimate for the treatment variable, if the selection covariates have explanatory power for the outcome variable. This strategy of including controls to increase precision is used similarly in the evaluation of experimental data.

Effects of weighting

I carry out a number of tests to illustrate the effects of applying the weighting method to my data.

The first effect is that the weights reduce the correlations between the covariates and the treatment variable. Table B.2 checks covariates balance before and after adjusting for the weights. As we can see, after the adjustment, the treatment and covariates correlations are substantially reduced, suggesting that given the weighting adjustment, the treatment variable becomes almost uncorrelated with the selection covariates that directly affect skill resettlement.

Table B.2: *Covariates' correlations with the treatment variable before and after applying the weights*

	Unweighted	Weighted
Unimpacted cohort skilled share	-0.71	0.03
	(0.00)	(0.60)
Nonagricultural population share	-0.54	0.01
	(0.00)	(0.80)

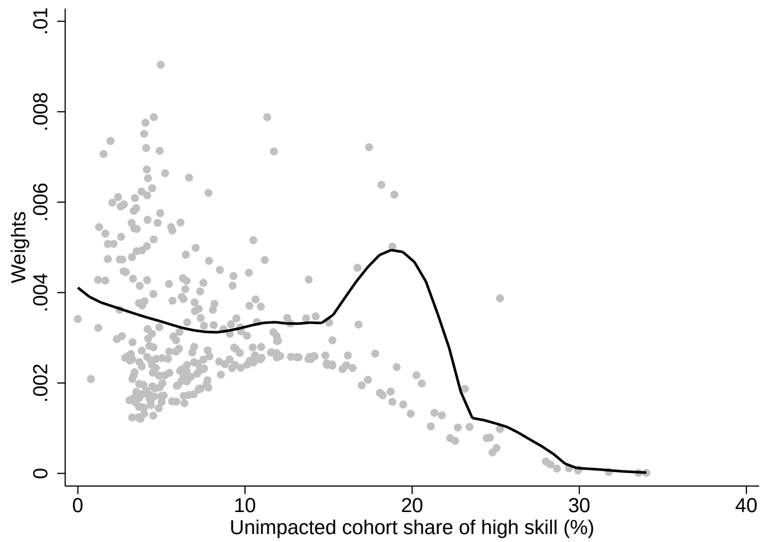
Notes: P-values in parentheses. This table shows the correlations between the treatment variable, the skill resettlement rate, and the selection covariates before and after applying the weights. The weights are calculated as in Fong, Hazlett and Imai (2017).

Another effect is that the weighting method assigns smaller weights to observations with few comparable other observations. Figure B.2 shows the scatterplots of weights against the selection covariates, as well as the local polynomials.

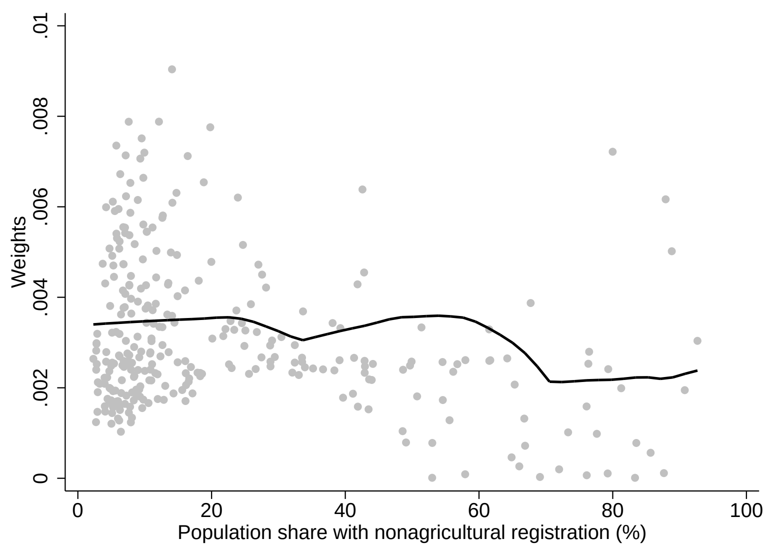
A key point worth emphasizing is that smaller weights are assigned to observations where comparable observations are scarcer, not where the probability densities are smaller. This explains why the local polynomial in Figure B.2b is much flatter than the one in Figure B.2a. In fact, if we compare Figures 3 and B.4, we see clearly that although the nonagricultural population share has very small density at high values as for the unimpacted cohort skilled share, it has much larger variance in treatment, as a result those observations with high nonagricultural population shares can still be matched with other observations with similar characteristics.

Lastly, I also apply the Frisch-Waugh-Lovell theorem to investigate what drives the differences between the OLS and WLS results. This exercise is discussed in more detail in Section B.2 after I present the OLS results.

Figure B.2: *Scatterplot and local polynomial of weights against selection covariates*



(a) *Unimpacted cohort skilled share*

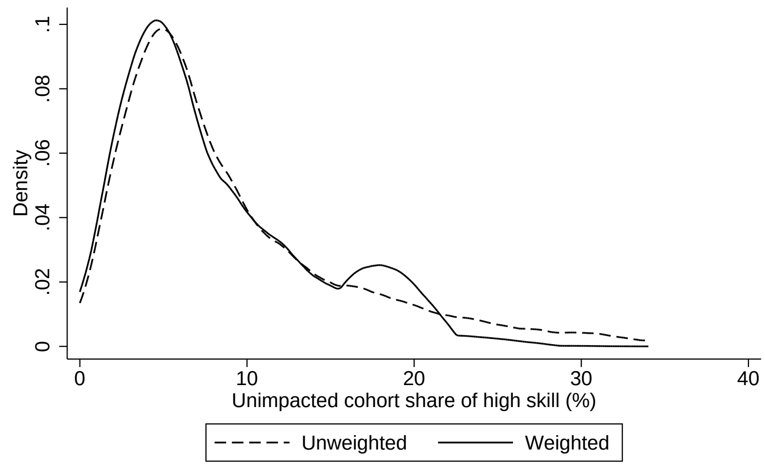


(b) *Nonagricultural population share*

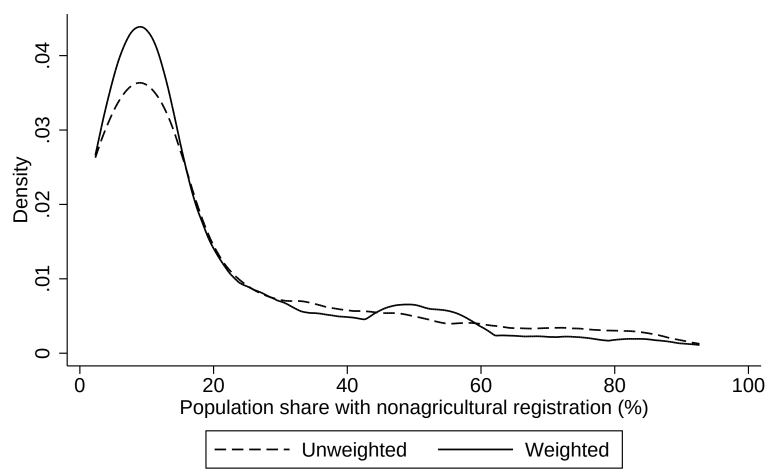
B.2 OLS vs. WLS: Applying the Frisch-Waugh-Lovell theorem

I apply the Frisch-Waugh-Lovell (FWL) theorem to investigate what drives the difference between OLS and WLS. To illustrate the difference, I pick *pop growth 1982–2000* as the outcome variable, since for this outcome variable, using WLS not

Figure B.3: *Weighted and unweighted kernel densities of selection covariates*



(a) *Unimpacted cohort skilled share*



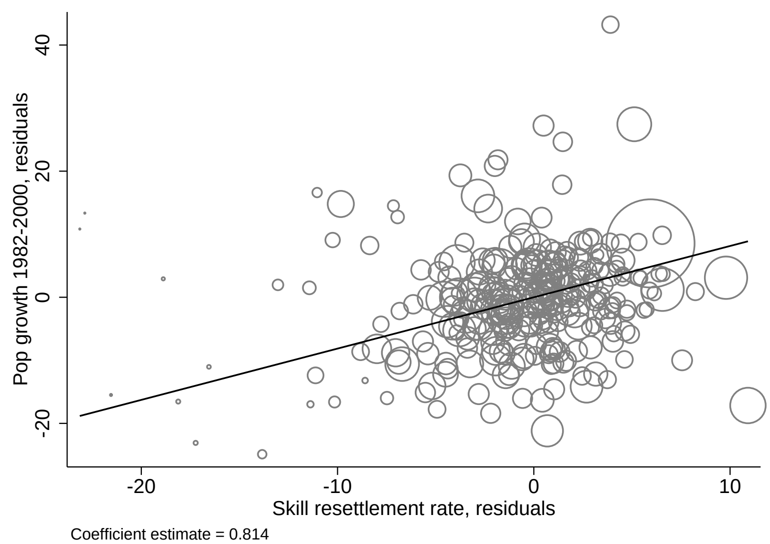
(b) *Nonagricultural population share*

only changes the point estimate substantially, but also has a big impact on standard errors (WLS statistically significant at 1%; OLS not statistically significant).

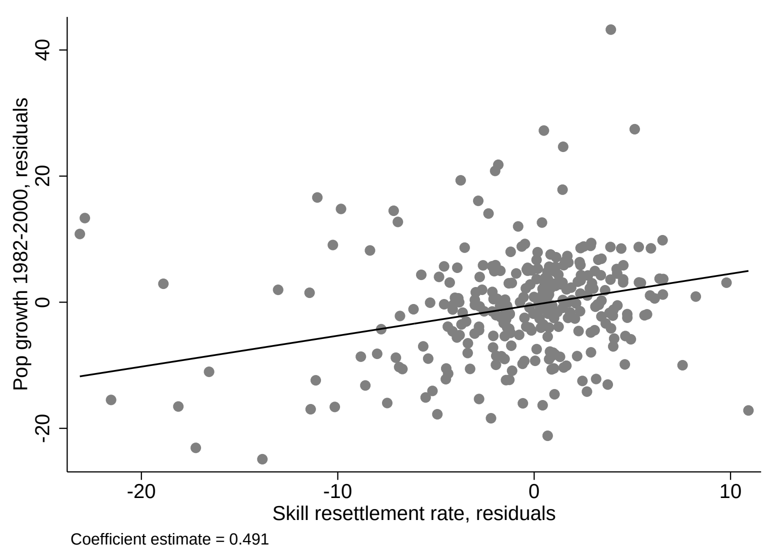
Note that in order to obtain the correct WLS point estimate, we need to use the observation weights in both stages of FWL. Figure B.4a shows the second stage of WLS with weights, which gives the correct WLS point estimate. Figure B.4c shows the second stage of OLS.

In comparison, Figure B.4b shows the second stage of WLS without weights. The weighting method does have an impact on the point estimates – those observations with small residual skill resettlement rates have small weights; on the other hand, OLS assigns these observations equal weights as other observations.

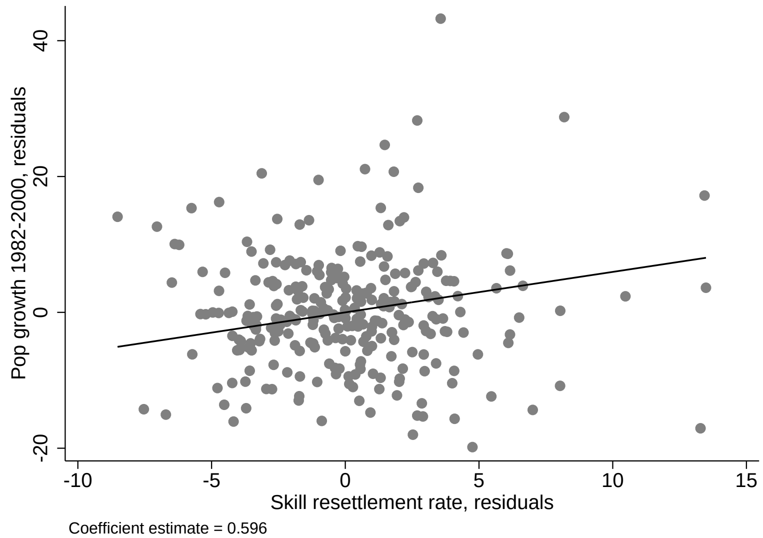
Figure B.4: *Scatterplots of second stage of the Frisch-Waugh-Lovell theorem*



(a) *WLS, when weighted in second stage*



(b) *WLS, when unweighted in second stage*



Pop growth 1982-2000, residuals
-20
0
20
40
-10
-5
0
5
10
15
Skill resettlement rate, residuals
Coefficient estimate = 0.596

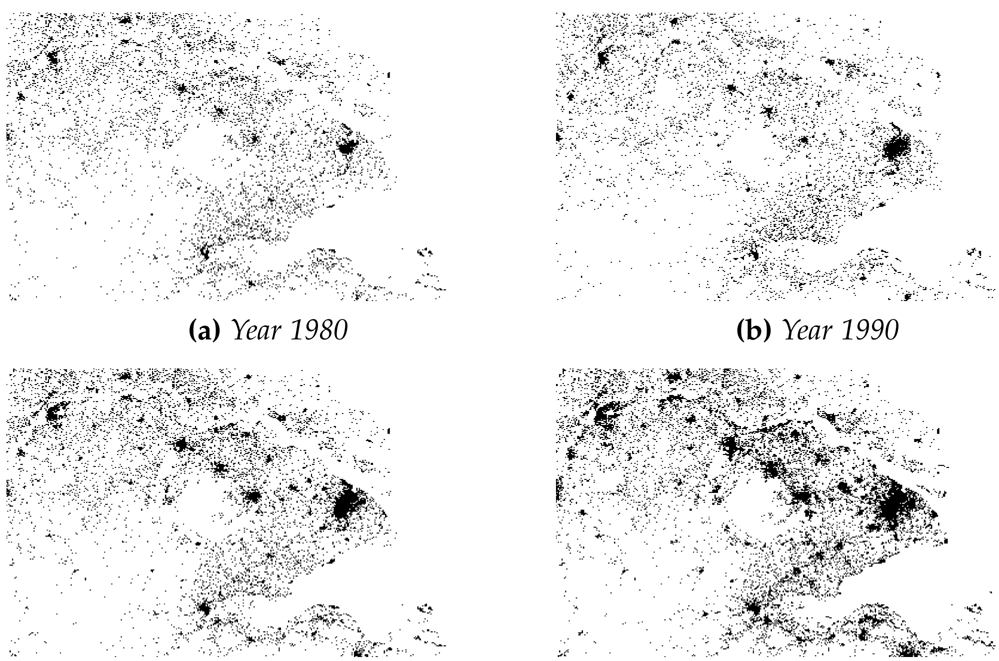
(c) *OLS*

C Appendix: Additional empirical results

C.1 Urban land use

China changed its accounting system of national accounts from Soviet Union's MPS system to the international standard SNA system in August 1992. As a result of this change, there may exist inconsistency in output accounting across Census years from 1982 to 2010. In addition, because output statistics are directly tied to politicians' promotions under the Chinese communist system, there have been considerable concerns about the quality of the output data. To address these concerns on the output data, I use land use as an additional proxy of economic activities to quantify local economic outcomes. The land use data are provided by the Institute of Geographic Sciences and Natural Resources Research of Chinese Academy of Sciences.

Figure C.5: *Satellite images of urbanized and industrialized land for the region around Shanghai, 1980-2010*



(a) *Year 1980* **(b)** *Year 1990*

(c) *Year 2000* **(d)** *Year 2010*

Notes: Areas in black indicate urbanized and industrialized land. Data sources: Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences.

Figure C.5 illustrates my land use data. All land is categorized according to how the land is used. I focus on the total land area that is urbanized or industrialized. Pixels in black in these figures represent urbanized and industrialized land.

Table C.3 reports results of skill resettlement rate on urban land use growth. The results are broadly consistently with results on productivity growth (Table 7), which report negative though insignificant effects. In comparison, the results on urban land use growth are negative and statistically significant. One caveat for the land use data is that land use is an intensive-margin measure for urban economic activities; it does not differentiate the intensities at which urbanized land is being used. We can interpret the results in Table C.3 as follows: Regions that received more high-skilled people lagged in the expansion of their urban footprints. Combining these results with the results on population growth which are positive, we see that skill resettlement caused a densification of urban population.

Table C.3: *Effects on urban land use growth*

	Urban land growth
Panel A. 1982-1990	
Skill resettlement rate	−4.955
	(7.255)
R^2	0.290
Panel B. 1982-2000	
Skill resettlement rate	−7.961**
	(3.616)
R^2	0.569
Panel C. 1982-2010	
Skill resettlement rate	−17.906***
	(5.933)
R^2	0.600
Number of prefectures	295

Notes: Robust errors in parentheses, clustered at the province level. Growth rates are normalized to decadal growth. Regressions weighted by weights calculated as in Fong, Hazlett and Imai (2017). Selection covariates are log population density in 1964, unimpacted cohort's skilled share, and population share with nonagricultural registration in 1964. Geographic characteristics include prefecture's average elevation. Infrastructure characteristics are distance to the nearest 1962 rail, and total length of 1962 highway within prefecture. Administrative indicators include an indicator for pre-1982 special economic zone (SEZ) designation, and an indicator for provincial capitals. Statistical significance denoted by * 10%, ** 5%, *** 1%.

Appendix References

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