

Three Papers on Economic Inequality and Social Mobility

by

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DEDICATION

This dissertation is dedicated to my wife, Qiang Wang.

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CHAPTER I Introduction

Social scientists have long sought to understand how economic inequality and social mobility change over time or vary across societies. As far back as the 1950s, economist Simon Kuznets advanced the hypothesis that income inequality first increases and then declines in the course of economic development, which has been famously known as the Kuznets curve (Kuznets 1955). On the other hand, sociologists have proposed different explanations for cross-national variations in intergenerational social mobility. For instance, the “thesis of industrialism” predicts that the more industrialized a society, the higher the degree of social fluidity (Blau and Duncan 1967; Treiman 1970). Furthermore, it has been suggested that state socialist countries and welfare states may exhibit more intergenerational mobility than liberal democracies (Giddens 1973; Parkin 1971). To test these hypotheses, empirical studies have largely relied on cross-national comparisons at a point in time (e.g., Grusky and Hauser 1984). This approach, however, is methodologically flawed because the observed effects of economic development and political institution may be confounded by the influences of unobserved, country-specific historical and cultural factors.

A more conservative strategy, therefore, is to look at temporal trends in a single country. In this regard, an excellent candidate for which the above questions can be addressed is China, as the country has experienced rapid industrial expansion as well as the demise of socialism since its economic reform that began in 1978. Income inequality in China has also grown tremendously over the past three decades: the Gini coefficient increased from 0.3 in 1980 to 0.55

in 2012. Why has inequality increased so much in China? How has it been connected to industrialization, marketization, and educational expansion? What about trends in social mobility? Has it declined due to China's institutional transition from state socialism to a market economy, or has it increased due to China's rapid industrialization? This dissertation represents my effort to answer these questions.

In Chapter II, I investigate how the rise of earnings inequality in urban China has been shaped by three large-scale structural changes in the labor force since the mid-1990s: (1) the expansion of tertiary education; (2) the decline of state sector employment; and (3) a surge in rural-to-urban migration. Based on data from two nationally representative surveys, I use variance function regressions to decompose the growth in earnings inequality from 1996 to 2010 into four components: changes in between-group earnings gaps, changes in within-group earnings variation, and two types of composition effects (*distribution effect* and *allocation effect*). I also employ counterfactual simulations to evaluate the utility of different explanations. Results show that nearly half of the growth in earnings inequality during this period is due to increases in returns to education, and that the other half can be attributed to compositional changes in the labor force. The composition effects stem chiefly from the expansion of tertiary education and the shrinkage of state sector employment.

Chapter III examines long-term trends in intergenerational social mobility. Analyzing intergenerational data from six comparable, nationally representative surveys between 1996 and 2012, I uncover two countervailing social mobility trends in post-revolution China. On the one hand, there is evidence of a decline in social fluidity following China's transition from state socialism to a market economy, as the link between origin and destination in vertical social status has significantly strengthened. On the other hand, horizontal mobility between the agricultural

and nonagricultural sectors has increased sharply during the country's rapid industrialization. Despite its recent decline, social fluidity in China is still much higher than that in mature capitalist societies. Moreover, cross-national comparisons reveal that a faster pace of industrialization is associated with greater horizontal mobility between the farming and nonfarming classes. Finally, mobility in China is characterized by disproportionate flows between the farming and the managerial/professional classes and between farming and self-employment—patterns that are unique products of the Chinese household registration (*hukou*) system.

The final chapter (chapter IV) proposes a methodological innovation that facilitates spatial and temporal comparisons in social mobility. I develop a shrinkage estimator of the log odds ratio for comparing mobility tables. Building on an empirical Bayes framework, the shrinkage estimator improves estimation efficiency by “borrowing strength” across multiple tables while placing no restrictions on the pattern of association within tables. Numerical simulation shows that the shrinkage estimator outperforms the usual maximum likelihood estimator (MLE) in both the total squared error and the correlation with the true values. Moreover, the benefits of the shrinkage estimator relative to the MLE depend on both the variation in the true log odds ratio and the variation in sample size among mobility regimes. To illustrate the effects of shrinkage, I contrast the shrinkage estimates with the usual estimates for the mobility data assembled by Hazelrigg and Garnier (1976) for 16 countries in the 1960s and 1970s. For mobility tables with more than two categories, the shrinkage estimates of log odds ratios can also be used to calculate summary measures of association that are based on aggregations of log odds ratios. Specifically, I construct an adjusted estimator of the Altham index, and, with a set of calibrated simulations, demonstrate its usefulness in enhancing both the

precision of individual estimates and the accuracy of cross-table comparisons. Finally, using two real data sets, I show that in gauging the overall degree of social fluidity, the adjusted estimator of the Altham index agrees more closely with results from the Unidiff model than does the direct estimator of the Altham index.

CHAPTER II Increasing Returns to Education, Changing Labor Force Structure, and the Rise of Earnings Inequality in Urban China, 1996-2010

Since its beginning in 1978, China's market-oriented reform has brought not only unprecedented economic growth but also a tremendous increase in economic inequality. In 1980, the Gini coefficient for family income in China was around 0.3 (UNU-WIDER 2008), but now it has reached the alarming level of 0.55 (Xie and Zhou 2014), a magnitude that places China among the most unequal societies in the world. While it is widely recognized that economic inequality in China is marked by a large rural-urban gap in industrial development (Knight and Song 1999; Sicular et al. 2007; Yang and Zhou 1999), recent survey data indicate that inequality within urban areas has also widened considerably over the past two decades (Jansen and Wu 2012; Li, Sato, and Sicular 2013). As shown in Figure II.1, the Gini coefficient for individual earnings climbed from 0.40 in 1996 to 0.49 in 2010. The pace of this growth is striking when we consider that it took 27 years for the corresponding measure in the U.S. to increase by the same proportion: from 0.33 in 1979 to 0.41 in 2006 (McCall and Percheski 2010).

What are the sources of the rising inequality in urban China? How has the change in aggregate inequality been driven by changes in individual and contextual determinants of earnings? Previous research has discussed three major mechanisms: (1) widening regional disparities (e.g., Hauser and Xie 2005), (2) increasing returns to education (e.g., Jansen and Wu 2012; Zhao and Zhou 2002), and (3) growing residual inequality (e.g., Hauser and Xie 2005; Meng, Shen, and Xue 2013). Few studies, however, have explicitly examined the role of

changing labor force structure in the evolution of earnings inequality in China. Indeed, since the mid-1990s, the composition of the urban labor force has been dramatically altered by three large-scale structural changes: (1) the expansion of tertiary education, (2) the decline of state sector employment, and (3) a surge in rural-to-urban migration. This article investigates whether, to what extent, and in what ways these institutional and demographic shifts have shaped the recent upswing of earnings inequality in urban China.

To accomplish this goal, I capitalize on variance function regressions (Western and Bloome 2009) to decompose the change in earnings inequality from 1996 to 2010 into four components: changes in between-group earnings gaps, changes in within-group earnings variation, and two types of composition effects. I also use counterfactual simulations to adjudicate between the competing explanations for the rise of inequality. Results show that nearly half of the growth in earnings inequality during this period is due to increases in returns to education, and that the other half can be attributed to compositional changes in the labor force. The composition effects result chiefly from changes in educational distribution and in sectoral structure, which have in turn been driven by the expansion of tertiary education and the shrinkage of state sector employment.

Although focusing on the context of urban China, the present study sheds light on the evolution of earnings inequality both in other developing countries and in other post-socialist states. On the one hand, a sizable body of research—in both sociology and economics—has investigated the linkage between educational distribution and aggregate inequality in earnings (Jacobs 1985; Knight and Sabot 1983; Lam and Levison 1992; Nielsen and Alderson 1997). It might be supposed that an expansion in college education would necessarily reduce the level of inequality in a developing country. However, researchers have concurred that an increase in the

supply of highly educated workers can actually drive up aggregate inequality through a more dispersed educational distribution, unless this effect is offset by a drop in returns to education. My analyses lend empirical support to this proposition by showing a substantial contribution of college expansion to the rise of inequality in urban China. On the other hand, like China, the post-socialist countries of Central and Eastern Europe (CEE) have also downsized their state sectors through various forms of privatization, a process that has also been related to observed increases in economic inequality. For example, based on cross-national comparisons, Bandelj and Mahutga (2010) report a positive effect of the degree of privatization on the level of income inequality in CEE. By analyzing trends from micro-level data, the present study not only demonstrates this link in China, but, as we will see, also measures the impact of state sector downsizing on earnings inequality over the past decade and a half.

Existing Explanations

In the course of China's post-socialist transition, the rise of earnings inequality has been propelled by a wide array of social, economic, and demographic processes. Here I review three mechanisms that have been extensively discussed in the literature: widening regional disparities, increasing returns to education, and growing residual inequality.

Widening Regional Disparities

Economic inequality in China has long been characterized by its vast regional disparities. Back in the Mao era, different regions already varied greatly in their pace of industrialization (Kanbur and Zhang 2005). During earlier years of the market-oriented reform, regional inequality slightly narrowed; yet it widened again over the 1990s, mainly due to a persistent gap in growth rates between the coastal and the inland provinces (Wan 2007). In fact, at the outset of the economic

reform, a number of coastal cities (known as Special Economic Zones) were granted preferential policies, such as tax breaks and duty exemptions, to attract both domestic and foreign investments. Thanks to these policies, coastal provinces such as Guangdong immediately enjoyed rapid growth in both foreign direct investments (FDI) and exports. These initial benefits, combined with economies of scale, soon translated into cumulative advantages (Démurger et al. 2002; Golley 2002). The coastal provinces, as a result, sustained higher growth rates than the inland provinces for a long time, leading to an ever-increasing coastal-inland divide. Inequality in economic development caused differentiation in personal earnings. As Xie and Hannum (1996) have shown, by 1988 the most influential predictor of earned income in urban China was not individual attributes but rather regional indicators. In a follow-up study, Hauser and Xie (2005) report that the influence of regional differences on earnings determination increased from 1988 to 1995. While more recent trends remain unclear, there is strong evidence that regional disparities persisted, if not widened, into the 2000s. Using the 1% population sample survey of 2005, Zhang and Wu (2010) find that 41% of the total variation in earnings can be explained by between-county differences.

To the extent that regional gaps have widened during the period under investigation, this article aims to identify how much of the observed rise in earnings inequality is attributable to increased regional gaps. To accomplish this goal, I base my counterfactual analyses on multiple regressions that control for educational attainment and other individual attributes. This procedure helps eliminate the influence of potentially confounding factors, such as increasing returns to education, a process that would exacerbate regional inequality if human capital was distributed unevenly across regions.

Increasing Returns to Education

The growth in earning inequality may also be explained by increasing returns to education. For earlier years of China's economic reform, returns to schooling have been found to be extremely low, which has been largely attributed to the absence of markets (Peng 1992; Walder 1990; Whyte and Parish 1985; Xie and Hannum 1996; Zhao and Zhou 2002). Nonetheless, the gradual expansion of markets has led theorists to predict an increase in the importance of human capital in the long term (Cao and Nee 2000; Nee 1989, 1991, 1996). This prediction has been widely supported by subsequent empirical studies (Bian and Logan 1996; Hauser and Xie 2005; Wu and Xie 2003; Zhou 2000). For instance, Hauser and Xie (2005) find that net returns to schooling in urban China almost doubled from 1988 to 1995. Jansen and Wu (2012) also demonstrate a steady increase in returns to schooling over the reform period: "one additional year of schooling translated into a 2 percent net increase in income in 1978, 3.5 percent in 1985, 4.5 percent in 1990, 5.5 percent in 1995, 6.6 percent in 2000, and 7.7 percent in 2005." However, in 1999, the Chinese government launched a college expansion project that has significantly raised college enrollments over the following years. As a result, the supply of college-educated workers has increased rapidly, which may have slowed down the growth in returns to education (Meng et al. 2013).

How would an increase in returns to education influence the size of earnings inequality? Xie and Hannum (1996) show that, holding constant the marginal distribution of human capital, an increase in returns to schooling generally drives up total inequality. Thus I expect the rise of inequality during the study period to be partly driven by an increase in returns to education, although the size of this increase since the early 2000s may have been moderated by an

expanding supply of college-educated workers. As with changing regional gaps, the impact of changing returns to education will be assessed by counterfactual analyses.

Growing Residual Inequality

Beyond changes in observed determinants of earnings, another explanation for the rise of earnings inequality is growing residual variation. Labor economists studying inequality in the U.S. have found that the rise of wage inequality in the 1970s and 1980s was primarily due to an increased residual variance of earnings after individual-level predictors such as schooling, experience, and demographic attributes are factored in (Juhn, Murphy, and Pierce 1993). This finding has been closely linked to the theory of “skill-biased technological change” (henceforth SBTC), which posits that the growth in residual inequality is mainly a result of rising returns to unobserved skills among workers with the same observed characteristics (Acemoglu 2002). Similarly, the rise of earnings inequality in urban China from the late 1980s to the mid-1990s has also been related to an increase in residual variation (Hauser and Xie 2005).

While traditional regression-based analyses assume homoscedasticity and thus regard residual variance as uniform among all individuals, recent research on inequality has begun to address heterogeneity in residual variance across population subgroups (Lemieux 2006; Western and Bloome 2009). When this heterogeneity is taken into account, the change in total residual inequality over a time period consists of two components: one represents changes in residual inequality among people in the same observed groups, and the other represents the effect of changing group proportions. Indeed, Lemieux (2006) challenges the SBTC explanation by showing that the growth of residual inequality in the U.S. during the 1990s was propelled mainly by changes in the proportion of workers in different experience-education cells rather than by changes in within-cell variation. In this study, I also separate out these two drivers of residual

inequality by modeling sectoral differences in residual variation in China. Specifically, I consider changes in within-sector variation as essential changes in residual inequality, and use *allocation effect* to denote the impact on residual inequality of changes in sectoral composition. For example, if inequality is greater in the private sector than in the state sector, a shift in the workforce from the state sector to the private sector can amplify the level of overall inequality through an allocation effect.

A Missing Link: Composition Effects

Among the above explanations, widening regional disparities and increasing returns to education can be construed as changing earnings gaps between population subgroups (in these cases, based on region and education), whereas growing residual inequality reflects increases in within-group variation. If the composition of the labor force is fixed, all sources of change in overall inequality can be subsumed under these two categories. Nonetheless, when group proportions are time-varying, trends in aggregate inequality may also be driven by composition effects. In fact, since the mid-1990s, the composition of the labor force in urban China has been dramatically reshaped by three large-scale socio-economic changes: (1) the expansion of tertiary education, (2) the decline of state sector employment, and (3) a surge in rural-to-urban migration (for more details, see Figure II.2). Below I discuss how these compositional shifts may have contributed to the rise of earnings inequality during the past two decades.

Expansion of Tertiary Education

In 1999, as noted above, the Chinese government instituted a college expansion policy that has significantly enlarged the pool of college-educated workers over the ensuing years. The purpose of this policy was two-fold. First, it was aimed to increase the supply of skilled labor for

sustaining China's rapid economic growth. Second, the extension of schooling for the youth was designed as a strategy to alleviate the pressure of re-employment for those being laid off during the reform of state-owned enterprises (see the next subsection). Coupled with cohort replacement, the expansion of higher education has, since 2003, substantially changed the educational distribution among the urban workforce. In 2003, those who had finished at least a three-year college constituted only 9.1% of the urban population (aged 6+); but by 2010, this portion had more than doubled to 21.5% (see Figure II.2).

What is the implication of such a compositional shift for earnings inequality? Before the college expansion, the educational distribution among urban workers was highly concentrated at the levels of junior and senior high school, suggesting a relatively homogeneous labor force in terms of observed skills. However, as more youths were provided the opportunity of obtaining a college degree, cohort replacement has resulted in a more dispersed educational distribution, which, everything else being equal, should have inflated earnings inequality in the aggregate. Thus we would expect that *the rise of earnings inequality in urban China can be partly attributed to changes in educational distribution.*

Shrinkage of State Sector Employment

As with other post-socialist countries, one central aspect of China's economic transition has been the decline of state sector employment. Although the economic reform in urban China started as early as 1984, it was concentrated on the goods market during its first decade. In the early 1990s, the vast majority of urban workers were still employed in state-owned enterprises (henceforth SOE), the prototypical work unit in pre-reform urban China. By 1994, however, most of the SOEs had excessive employment and nearly half were incurring losses, severely hindering China's economic development (Cao, Qian, and Weingast 2003). To remedy this problem, the

Chinese government has, since 1995, been reforming and downsizing state-owned enterprises under the policy of “grasp the large and let go the small.” On the one hand, the central government began to merge and restructure large SOEs, thereby consolidating its control over certain strategically vital industries, such as power generation, telecommunications, and raw materials. On the other hand, at the local level, small SOEs were largely privatized, and workers in medium-sized SOEs were massively laid off. As a result, since the mid-1990s, tens of millions of former SOE employees have been pushed into the private sector. Among new entrants to the labor market, the share of state sector employment has also dwindled. Such an imbalance between exit and entry has caused a steady decline in state sector employment during the past two decades: in 1996, 64% of the urban workers were employed in the state sector, but by 2010 this figure had reduced to 27% (see Figure II.2).

It is widely acknowledged that SOE reform has been successful in vitalizing China’s market economy. At the same time, however, the massive transfer of workers from the state sector to the private sector may have exacerbated the country’s earnings distribution. Before the reform, the majority of urban workers were employed by the state with a centrally-planned wage system, which imposed a highly compressed earnings distribution. Earnings variation within the state sector was driven primarily by differences in bonus income, which depended heavily on the profitability of particular work units (Wu 2002; Xie and Wu 2008). Overall, earnings inequality was substantially lower in the state sector than in the private sector, partly because observed and unobserved skills were less rewarded by the state, and partly because the paychecks of state employees were less sensitive to the ebb and flow of the market. This pattern, in fact, has been fairly stable over time. Today’s SOEs in China continue to benefit from sheltered markets, implicit government subsidies, and politically favored bank loans. By shielding the SOEs from

market competition, these institutional protections have sustained a relatively low dispersion of earnings across the state sector. Meanwhile, the downsizing of SOEs has pushed tens of millions of workers into the private sector, where their heterogeneity in ability and skills is more likely to translate into different rates of pay. Therefore, given that earnings inequality is lower in the state sector than in the private sector, we would expect that *the massive transfer of workers from the state sector to the private sector has contributed to the rise in aggregate inequality.*

Rural-to-urban Migration

In the pre-reform era, rural-urban migration in China was severely restricted by the Chinese household registration system, i.e., *hukou*, a state institution established to limit population mobility. Since 1978, the market reform has moderately eased the restriction on temporary migration, but without a corresponding relaxation of the *hukou* system. This has resulted in a “floating population” of urban dwellers with rural *hukou* status (Wu and Treiman 2004). The size of this floating population was relatively small, if not negligible, until the early 1990s. Since then, China’s economic growth has been increasingly propelled by export-oriented manufacturing sectors and government-sponsored infrastructure projects, which have significantly raised the demand for young and low-skilled workers in many urban centers. The surge of demand for cheap labor has attracted wave after wave of young and poorly-educated migrants from the rural inland. As a result, the volume of rural migrants residing in urban centers has increased tremendously over the past two decades. According to Meng et al. (2013), the number of rural-urban migrant workers was about 39 million in 1997, but by 2009 the size had increased to 145 million, constituting more than a quarter of the urban labor force.

Despite their growing contribution to the economic boom in urban areas, it remains extremely difficult for these rural migrants to acquire a local *hukou* in the cities where they work.

As noted by Chan and Buckingham (2008), in such large cities as Beijing, Shanghai and Guangzhou, which are the major destinations of recent waves of rural-urban migrants, the entry requirements for obtaining a local *hukou* are highly prohibitive and clearly beyond the reach of most migrant workers. The lack of local *hukou* status is perhaps the greatest disadvantage for this ever-increasing floating population because *hukou* status was and still is a very strong institutional constraint that shapes one's social and economic wellbeing in urban China (Treiman 2012; Wu and Treiman 2004, 2007). Not only is local *hukou* status a prerequisite for such social welfare benefits as health care and unemployment insurance, but migrant workers without a local *hukou* also suffer from a range of unfair treatments in the workplace, such as wage arrears and denial of payments.

Given the persistent power of *hukou* in shaping one's economic wellbeing, how has the recent upsurge in rural-to-urban migration affected earnings inequality in urban China? Meng and Zhang (2001) have shown that in the 1990s, migrant workers without an urban *hukou* were subject to a wage penalty in the urban labor market. It is unclear, however, whether such a wage gap narrowed or widened into the 2000s, and whether the wage gap necessarily translated into an earnings gap between the two groups (given that migrant workers typically work for longer hours and more days than local urban workers). Nonetheless, *to the extent that an earnings gap exists across the hukou axis, the surge in rural-to-urban migration should have subjected a larger share of the workforce to an earnings penalty, thereby aggravating the level of overall inequality.*

Methods

R²-based Methods

In this study, I use the variance of log earnings to gauge the size of earnings inequality. The variance measure is particularly useful for studying trends in inequality because it can be easily decomposed into between-group and within-group components using ANOVA (see Mouw and Kalleberg 2010). The ratio of the between-group component to the total variance provides an intuitive measure for the between-group contribution to total inequality, a measure that is equivalent to the R^2 in a linear regression of log earnings on group dummies. To examine temporal trends in the size of between-group contribution, one may simply track changes in this ratio over time. For example, Kim and Sakamoto (2008) used the time series of occupation R^2 to assess the relative importance of between-occupation and within-occupation inequality in explaining the rise of wage inequality in the U.S. Moreover, in a regression model that controls for additional covariates, we can evaluate the net contribution of a particular set of variables using incremental or partial R^2 s (see Kim and Sakamoto 2008; Meng et al. 2013). As a preliminary analysis, I also use partial R^2 to detect temporal variations in the importance of different earnings determinants.

This approach, however, is prone to conflate changes in population composition with *real* changes in between-group disparities and in within-group variation. To see this, consider a hypothetical population consisting of only two groups: college graduates and high school graduates. Assume that the average gap in log earnings between the two groups is fixed, and that the within-group variation among college graduates is greater than that among high school graduates. Now imagine an education expansion that enlarges the share of college graduates from 10% to 50%. In this case, earnings inequality will increase, neither via increased returns to

education nor via increased within-group inequality, but via a change in population composition. Specifically, the impacts of this compositional shift are two-fold. On the one hand, given an earnings premium for college graduates, a more balanced distribution of the two groups will automatically inflate the overall variance. On the other hand, given that within-group inequality is higher among college graduates than among high school graduates, an increased share of the former will also raise the level of total inequality. The R^2 measure, however, may drift in either direction without a clear interpretation.

Variance Function Regressions and Decomposing Trends in Inequality

My analytical focus is to disentangle different sources of the observed rise in earnings inequality, thus adjudicating between the competing explanations discussed in the preceding sections. To achieve this goal, I decompose the change in the variance of log earnings based on variance function regressions (Western and Bloome 2009), a technique that allows both the mean and the variance of log earnings to depend on a set of explanatory variables.

To sketch this approach, let us denote by Y_t the dependent variable, log earnings, at time t . Meanwhile, denote by X_t and Z_t two sets of independent variables that predict the mean and the variance of log earnings, respectively. We then jointly estimate the conditional mean and the conditional variance of log earnings as linear functions of X_t and log-linear functions of Z_t , yielding two fitted models:

$$\hat{E}(Y_t|X_t) = \hat{\beta}_t X_t, \quad \widehat{Var}(Y_t|Z_t) = \exp(\hat{\lambda}_t Z_t),$$

where $\hat{\beta}_t$ and $\hat{\lambda}_t$ represent estimated coefficients of X_t and Z_t . As a result, the fitted total variance of log earnings can be written as

$$\hat{V}_t = \widehat{Var}[\hat{E}(Y_t|X_t)] + \hat{E}[\widehat{Var}(Y_t|Z_t)] = \widehat{Var}(\hat{\beta}_t X_t) + \hat{E}[\exp(\hat{\lambda}_t Z_t)]. \quad (1)$$

This equation can be seen as a parametric analog of ANOVA, with the first component corresponding to between-group inequality and the second component within-group inequality. Accordingly, the change in total inequality from time t to another time point t' ($t < t'$) can be written as

$$\hat{V}_{t'} - \hat{V}_t = \widehat{Var}(\hat{\beta}_{t'}X_{t'}) - \widehat{Var}(\hat{\beta}_tX_t) + \hat{E}[\exp(\hat{\lambda}_{t'}Z_{t'})] - \hat{E}[\exp(\hat{\lambda}_tZ_t)], \quad (2)$$

where the first contrast $\widehat{Var}(\hat{\beta}_{t'}X_{t'}) - \widehat{Var}(\hat{\beta}_tX_t)$ measures the change in between-group inequality, and the second contrast $\hat{E}[\exp(\hat{\lambda}_{t'}Z_{t'})] - \hat{E}[\exp(\hat{\lambda}_tZ_t)]$ measures the change in within-group inequality. These two parts can be further decomposed to separate the effects of changing coefficients (β and λ) from those of changing distributions of X and Z . Specifically, equation (2) can be expanded as

$$\hat{V}_{t'} - \hat{V}_t = \hat{\delta}_B + \hat{\delta}_D + \hat{\delta}_W + \hat{\delta}_A, \quad (3)$$

with

$$\hat{\delta}_B = \widehat{Var}(\hat{\beta}_{t'}X_t) - \widehat{Var}(\hat{\beta}_tX_t)$$

$$\hat{\delta}_D = \widehat{Var}(\hat{\beta}_{t'}X_{t'}) - \widehat{Var}(\hat{\beta}_{t'}X_t)$$

$$\hat{\delta}_W = \hat{E}[\exp(\hat{\lambda}_{t'}Z_t)] - \hat{E}[\exp(\hat{\lambda}_tZ_t)]$$

$$\hat{\delta}_A = \hat{E}[\exp(\hat{\lambda}_{t'}Z_{t'})] - \hat{E}[\exp(\hat{\lambda}_{t'}Z_t)].$$

In this decomposition, the first term, δ_B , measures the change in between-group earnings gaps. For example, if region is the only predictor of earnings, then δ_B represents the impact of widening (if $\delta_B > 0$) or narrowing (if $\delta_B < 0$) regional gaps on total inequality. The second term, δ_D , gauges the change in between-group inequality due to changes in population composition. Recent research on the U.S. labor market has revealed a polarization of the occupational structure, i.e., growing employment in both high- and low- paying occupations and hollowing out of the middle (Massey and Hirst 1998; Mouw and Kalleberg 2010). Such compositional

changes would drive up overall inequality even if between-occupation differences in average earnings were fixed. For this reason, I refer to δ_D as *distribution effect*. Clearly, changes in between-group gaps (δ_B) and the distribution effect (δ_D) together constitute the total change in between-group inequality ($\delta_B + \delta_D$). The third term, δ_W , characterizes the change in within-group variation among people with the same observed characteristics. In the economics literature, this component is intimately connected with the theory of SBTC, which stresses the role of increasing returns to skills (often unobserved) in the growth of residual inequality. The last term, δ_A , identifies the change in within-group inequality due to changes in population composition. As discussed in the preceding section, the massive transfer of workers from the state sector to the private sector in urban China may have raised overall inequality as a result of unequal residual variations between the two sectors—even if the amounts of within-sector inequality stayed unchanged over time. Hence I term δ_A *allocation effect*. The separation of the allocation effect from δ_W enables us to distinguish the impacts of compositional shifts in the labor force from more inherent changes in residual inequality. The structure of this four-component decomposition is shown concisely in Table II.1.

Note that the above decomposition is not algebraically unique. In equation (3), the difference between $V_{t'}$ and V_t is decomposed in a way that changes in coefficients happen first and changes in population composition come second. Reserving this order yields an alternative decomposition. Below I use Type I decomposition to mean equation (3) and call the alternative Type II decomposition.

Counterfactual Analysis

Results from variance function regressions can be used to construct counterfactual levels of inequality, thus enabling us to assess the utility of competing explanations (Western and Bloome

2009). For example, to evaluate the effect of changing returns to education, we can calculate the following counterfactual:

$$\widehat{V}_{t'}^{\beta^{edu}=\widehat{\beta}_t^{edu}} = \widehat{Var}(\widehat{\beta}_{t'}^{-edu} X_{t'}^{-edu} + \widehat{\beta}_t^{edu} X_{t'}^{edu}) + \widehat{E}[\exp(\widehat{\lambda}_{t'} Z_{t'})], \quad (4)$$

where β^{edu} denotes the coefficient (or a set of coefficients) for education, and β^{-edu} denotes the coefficients for all other predictors. Equation (4) gauges the level of inequality that would have been observed at time t' had returns to education stayed at the level of time t . Thus the difference between $\widehat{V}_{t'}$ and $\widehat{V}_{t'}^{\beta^{edu}=\widehat{\beta}_t^{edu}}$ identifies the contribution of changing returns to education to the change in overall inequality from t to t' .

To assess the impact of a compositional shift, we can reweight the observed data at time t' to make the marginal distribution of the corresponding variable identical to that at time t (see Lemieux 2006). For instance, to gauge the effect of college expansion, we can fix the marginal distribution of educational attainment at time t by appropriately down-weighting college graduates and up-weighting others in the sample at time t' , i.e.,

$$\widehat{V}_{t'}^{\pi^{edu}=\pi_t^{edu}} = \widehat{Var}_{\pi_t^{edu}}(\widehat{\beta}_{t'} X_{t'}) + \widehat{E}_{\pi_t^{edu}}[\exp(\widehat{\lambda}_{t'} Z_{t'})], \quad (5)$$

where π_t^{edu} denotes the educational distribution at time t , and its appearance as subscript means that corresponding weights are used to calculate the variance and the expectation. The composition effect of changing educational distribution is thus identified by the difference

between $\widehat{V}_{t'}$ and $\widehat{V}_{t'}^{\pi^{edu}=\pi_t^{edu}}$:

$$\widehat{V}_{t'} - \widehat{V}_{t'}^{\pi^{edu}=\pi_t^{edu}} = \widehat{Var}(\widehat{\beta}_{t'} X_{t'}) - \widehat{Var}_{\pi_t^{edu}}(\widehat{\beta}_{t'} X_{t'}) + \widehat{E}[\exp(\widehat{\lambda}_{t'} Z_{t'})] - \widehat{E}_{\pi_t^{edu}}[\exp(\widehat{\lambda}_{t'} Z_{t'})].$$

The above expression reveals that the composition effect consists of two parts, representing changes in between-group and in within-group inequalities. Hence, the first part corresponds to the *distribution effect*, and the second part corresponds to the *allocation effect*.

While the above illustrations are for the variable of education, the same techniques can be employed to gauge the effects of changes in other determinants of earnings. Table II.2 shows how the competing explanations discussed earlier will be examined by counterfactual analysis. For example, I will assess the allocation effect of state sector shrinkage by reweighting the 2010 data such that the sectoral composition equals that in 1996. However, since the educational distribution may systematically differ across sectors, the reweighting method is unable to manipulate the marginal distribution of one variable without changing that of the other. Therefore, in the following analysis, I also examine the combined effects of changing educational and sectoral compositions by fixing their joint distributions at the 1996 level.

Data

I use data from two nationally representative sample surveys: the 1996 survey of “Life History and Social Changes in Contemporary China” (henceforth LHSCCC 1996) and the 2010 wave of the Chinese General Social Survey (henceforth CGSS 2010). Although these two surveys have different names, their data are highly comparable for my trend analysis. First, both surveys used a multi-stage stratified sampling design under which one adult was randomly selected from each sampled household (Li and Wang 2012; Treiman and Walder 1998). Second, in both surveys, the fieldwork was implemented by the same organization—the Department of Sociology at Renmin University of China. Moreover, the two surveys adopted the same rule to demarcate urban and rural populations—namely, whether the sampled household belonged to a neighborhood

committee (urban) or a village committee (rural)—which ensures that the two urban samples are consistent in their coverage.

While CGSS 2010 collected data from all 31 provinces of mainland China, the sampling frame of LHSCCC 1996 did not include Tibet. To maintain the comparability of labor markets over time, I excluded Tibet from the CGSS 2010 data as well (step 1: $N_{1996}=3087$, $N_{2010}=7081$). Since Tibet represents only 0.2% of the Chinese population (National Bureau of Statistics of China 2011), its exclusion is unlikely to weaken the representativeness of the data. To assess earnings inequality among the economically active population, I further restricted both samples to those who were between ages 20 and 69 and gainfully employed with annual earnings greater than 100 1996 Yuan (step 2: $N_{1996}=2024$, $N_{2010}=3050$).¹ After eliminating a small number of respondents with missing covariates, we have 2019 individual workers from LHSCCC 1996 and 3040 from CGSS 2010.

The dependent variable, earnings, refers to the total amount of earned income, including wages and salaries, bonuses, and profits from private businesses.² Earnings in 1996 are inflation-adjusted to 2010 Yuan based on official CPI rates (National Bureau of Statistics of China 2011). To adjudicate between the competing explanations for the rise of inequality, I use the following explanatory variables: province, level of education, sector of employment, and *hukou* status. To

¹ In this step, the sample size dropped more substantially for CGSS 2010 than for LHSCCC 1996. This is mainly due to their differences in fieldwork implementation rather than a substantial decline in labor force participation. According to data from the World Bank, the labor force participation rate in China dropped by only 4 percentage points during this period, from 75% in 1996 to 71% in 2010.

² In LHSCCC 1996, profits from private businesses were measured at the family-level. Hence I divided them by the number of working family members before treating them as a part of personal earnings.

better identify composition effects, I treat education as a categorical variable containing six levels of educational attainment: (1) no schooling, (2) elementary school, (3) junior high school, (4) senior high school or vocational high school, (5) vocational college, (6) four-year college or above. While most previous studies treated sector of employment as a state-market dichotomy, I adopt a tripartite typology of sector: (1) state sector, which includes government agencies, public organizations, and state-owned enterprises, (2) private sector, which includes domestic private enterprises, foreign-invested firms, joint ventures, as well as collective enterprises and institutions,³ and (3) self-employment. *Hukou* status is coded as a binary variable (non-agricultural vs. agricultural) in order to identify rural-urban migrants. The regression model for the mean of log earnings also includes sex, age, age squared, and party membership as covariates.

Table II.3 reports some descriptive statistics. The first two columns show the population share of different subgroups in 1996 and 2010. With regard to sex, age, and party membership, the group proportions are fairly similar across the two years, although the workforce appears slightly older in 2010. The share of workers holding a rural *hukou* increased sharply, from 12% in 1996 to 27% in 2010, reflecting the sheer scale of rural-to-urban migration. Thanks to college expansion, the proportion of workers who had a college degree (either vocational or regular) more than doubled. Moreover, state sector employment declined dramatically: in 1996, 59% of the workers were employed in the state sector, but by 2010 this portion had reduced to 27%.

The next two columns present the group-specific means of log earnings. Overall, we see a substantial increase in earnings for both men and women, both party members and non-members, and all age groups. However, on average, earnings growth seems larger for permanent urban

³ Collective institutions and enterprises typically do not receive financial support from the central and local governments. Compared with state-owned organizations, they are less regulated by the state and closer to market forces. Therefore they are classified into the private sector.

dwellers and more-educated workers than for rural-urban migrants and less-educated workers. The last two columns demonstrate the group-specific levels of inequality, measured by the variance of log earnings. We find that the rise of earnings inequality is greater among party members and permanent urban dwellers than among non-members and rural-urban migrants. Moreover, for both years, earnings dispersion is much lower in the state sector than in the private sector, and the self-employed exhibit the highest within-group inequality.

Results

Partial R^2 s from Conventional Regressions

To gauge the influence of a given set of variables on earnings inequality, past research has often relied on R^2 or partial R^2 from multiple regressions of log earnings. As discussed earlier, this approach is not well suited for studying trends in inequality because it is prone to conflate changes in population composition with inherent changes in between-group gaps and within-group variation. For a given time point, though, it can provide a snapshot of the structure of earnings inequality. In Figure II.3, the bar plots show the net contributions of province, education, sector of employment, and *hukou* status to the overall inequality, measured by the corresponding partial R^2 s. First, we find that province is the most influential factor shaping earnings inequality in urban China: in both years, nearly 15% of the variation in log earnings can be explained by interprovincial disparities, even after covariates such as sex, age, and education are controlled for. Second, we see a sharp increase in the importance of education: the partial R^2 grew from 4.7% in 1996 to 12.3% in 2010. Finally, sector of employment accounts for roughly 3% of total inequality at both time points, and the explanatory power of *hukou* status is negligible for both years.

The above results highlight the significance of region and education in maintaining earnings inequality in urban China. Nonetheless, they do not reveal the sources of the growth in inequality. For example, the rise in the partial R^2 of education could stem either from real increases in returns to education or from changes in educational composition (i.e., distribution effect). I now turn to results from variance function regressions, which provide a basis for both decomposition and counterfactual analyses.

Variance Function Regressions and Decomposition of the Rise in Inequality

Table II.4 reports the results from variance function regressions. The first two columns present the effects of different predictors on the mean of log earnings. First, for both years, we see an earnings penalty for females, a premium for party-members, and a quadratic effect of age, which are all consistent with previous research on earnings determination in urban China (e.g., Xie and Hannum 1996). However, we find that the effect of rural *hukou* is not significantly different from zero in either 1996 or 2010, indicating that there may not be an earnings penalty for rural-urban migrants when covariates, such as education and sector, are factored in. Meanwhile, we see a sharp rise in economic returns to a college degree (either vocational or regular) over this period: in 1996, a worker with a four-year college education was expected to earn 30% ($e^{0.264} - 1$) more than a worker with only a high school diploma; by 2010, this gap had widened to 84% ($e^{0.608} - 1$).⁴ In addition, for both years, we observe an earnings premium for workers in the state sector compared with employees in the private sector. The self-employed seem to have improved their position enormously: in 1996, they earned markedly less than the other two

⁴ As both estimated coefficients are asymptotically normal and independent, it is easy to show that the z-score for their difference, $\frac{\hat{\beta}_2 - \hat{\beta}_1}{\sqrt{\widehat{se}^2(\hat{\beta}_2) + \widehat{se}^2(\hat{\beta}_1)}}$, is highly significant.

groups, but by 2010 they had become the most advantaged group, earning about 20% ($e^{0.183} - 1$) more than state sector workers.

My earlier argument presumes that residual inequality is substantially lower in the state sector than in the private sector. To model sectoral differences in residual inequality, I use sector dummies as predictors in the variance regressions.⁵ As shown in the last two columns, estimated residual variation is much smaller in the state sector than in the private sector, and the self-employed are the most unequal group. This pattern holds true in both years, although to a lesser extent in 2010 than in 1996. This heterogeneity in residual variance underlies my hypothesis that the decline of state sector employment has raised the level of overall inequality through an allocation effect.

Based on the coefficient estimates in Table II.4, I decompose the change in inequality from 1996 to 2010 into the four components expressed by equation (3). The bar plots in Figure II.4 show the results from both Type I and Type II decompositions. We find that changes in between-group earnings gaps account for 34%-46% of the total growth in earnings inequality, depending on the way the decomposition is performed. Distribution effect (i.e., change in between-group inequality through compositional shifts) explains 22%-34% of the total growth, whereas allocation effect (i.e., change in within-group inequality through compositional shifts) contributes 21%-37%. Taking them as a whole, we conclude that more than half of the rise in inequality over this period is attributable to compositional shifts in individual and contextual characteristics. By contrast, the contribution of δ_W ranges from -5%-12%, suggesting that

⁵ Because there is no strong reason to assume differences in residual inequality across other social dimensions, sector of employment is used as the only predictor in the variance model.

changes in within-group dispersion have very small if any impact on the change in earnings inequality over this period.

Counterfactual Analyses: Evaluation of Competing Mechanisms

I now assess the utility of different explanations through counterfactual analyses. In Table II.5, the first column presents the variances of log earnings adjusted for changes in between-group gaps (i.e., β) and in within-group variation (i.e., λ), and the second column shows the counterfactual change from 1996 to 2010 when between-group/within-group effects are fixed at the 1996 level. The third column reports the percentage of the total change explained, that is, other things being equal, how much of the total rise in inequality would have disappeared had the corresponding between-group/within-group effects stayed unchanged during this period. First, fixing the coefficients of province dummies yields an adjusted variance of 0.839, suggesting that changing interprovincial disparities accounts for none of the total growth in inequality. In contrast, by fixing the coefficients of educational attainment, we find that rising returns to education explains 45.2% of the total growth. The next row shows that had all between-group earnings gaps stayed at the 1996 level, 45.8% of the increased inequality would have disappeared. A comparison of the above two numbers indicates that changes in between-group gaps are almost entirely driven by increases in returns to education. Finally, by fixing the coefficients in the variance model (λ), we find that changes in within-sector earnings variation have virtually no influence on the rise of inequality over this period.

Table II.6 shows the variances of log earnings adjusted for a range of compositional shifts and the corresponding contributions of distribution effects, allocation effects, and total composition effects. First, we find that the distribution effect of changing *hukou* composition is close to nil, which echoes the fact that rural *hukou* is not statistically significant in predicting log

earnings. In other words, because there is no discernible gap in earnings between rural-urban migrants and permanent urban workers, changing *hukou* composition has little impact on the trends in earnings inequality. Second, the distribution effect of education, which results chiefly from the college expansion policy, accounts for 21.9% of the total change in inequality. That is, more than a fifth of the increased variation in log earnings can be attributed to a more dispersed educational distribution.⁶ Third, the allocation effect of changing sectoral composition also explains about one fifth of the increased inequality. This finding demonstrates the crucial role of state sector shrinkage: Because within-sector variation is substantially lower in the state sector than in the private sector, the massive labor influx into the private sector has inflated earnings inequality in the aggregate.

Although we do not assume any effects of *hukou* and education on the variance of log earnings, both changing *hukou* composition and changing educational composition exhibit allocation effects as well. This is because the distributions of *hukou* and of educational attainment are not independent of the distribution of sector of employment. Indeed, according to the 2010 data, rural-urban migrants are more likely to work in the private sector than permanent urban workers, and college-educated workers are more likely to work in the state sector than other educational groups. Therefore, a down-weighting of rural-urban migrants will lower the average within-group inequality, whereas a down-weighting of college-educated workers will

⁶ Since the college expansion primarily benefitted the younger cohorts, age and education are fairly correlated in the 2010 data. Therefore the reweighting of the educational distribution inevitably altered the age structure, which may have biased the results. To alleviate this concern, I conducted auxiliary analyses by adjusting the *conditional distribution of education given age* (i.e., $\pi_{edu|age}$) such that the educational distribution resembles that in 1996 but the age distribution remains at the 2010 level. The results are substantively identical to those reported in Table 6.

heighten it. As a result, we observe a positive allocation effect of rural-urban migration and a negative allocation effect of changing educational composition. These allocation effects, however, should not be taken at face value because the compositional shifts of *hukou* and education may be closely intertwined with changes in sectoral structure. Hence I proceed to examine the combined effects of different compositional shifts by fixing the joint distribution of the corresponding variables at the 1996 level. In particular, by fixing the joint distribution of education and sector, we find that 41.9% of the total increase in inequality results from compositional changes in education and sector of employment. This number, not surprisingly, roughly equals the sum of the distribution effect of changing educational composition and the allocation effect of changing sectoral composition. Finally, when the joint distribution of all observed characteristics (i.e., the data matrices \mathbf{X} and \mathbf{Z}) is fixed at the 1996 level, the increased variance from 1996 to 2010 drops from 0.304 to 0.137, suggesting that 54.9% of the total growth in inequality is due to compositional shifts in individual and contextual characteristics. Of these composition effects, about three quarters ($41.9\%/54.9\%=76.3\%$) come from changing educational and sectoral distributions.

In short, the counterfactual analyses show that the rise of earnings inequality from 1996 to 2010 is primarily driven by (1) increases in returns to education, (2) a more dispersed educational distribution, and (3) changes in sectoral structure. In particular, the composition effects of (2) and (3) stem from the policy of college expansion and the institutional downsizing of state-owned enterprises.

Conclusion and Discussion

Earnings inequality in urban China has grown sharply over the past two decades. To account for the rise of inequality in urban China, prior studies have offered three major explanations:

widening regional gaps, increasing educational returns, and growing residual inequality. In this article, I examined how the recent upswing in earning inequality has been shaped by three large-scale structural changes: (1) college expansion, (2) state sector shrinkage, and (3) rural-to-urban migration. To adjudicate between existing explanations and these composition effects, I used variance function regressions to decompose and simulate the change in earnings inequality between 1996 and 2010. My results suggest that nearly half of the growth in earnings inequality during this period can be explained by increases in returns to education, and that the other half is attributable to compositional shifts in the labor force. The composition effects are mainly due to changes in educational and sectoral distributions, which in turn result from the expansion of tertiary education and the shrinkage of state sector employment.

Moreover, we find little effect of the upsurge in rural-urban migration on earnings inequality. In fact, my regression results show no significant difference in earnings between rural migrant workers and permanent urban workers once covariates, such as education and sector, are taken into account. This finding does not necessarily contradict earlier studies that demonstrate a wage penalty for rural migrant workers (Meng and Zhang 2001) because a wage penalty is not equivalent to a gap in total earnings—considering that rural migrants usually work for longer hours and more days than local urban workers. In addition, it is worth noting that although rural-urban migration seems to have limited impact on earnings inequality in urban China, it may have a profound influence on economic inequality in China as a whole. Assuming that migrant workers earn more in urban areas than they would in their rural origins, an increasing volume of migrant workers can narrow the gap between these two otherwise segregated and unequal

populations (i.e., urban and rural *hukou* holders), thereby reducing the level of nationwide inequality.⁷

Methodologically, this study illustrates the utility of variance function regressions, a technique recently proposed by Western and Bloome (2009), for studying trends in inequality. By simultaneously modeling the mean and the variance of log earnings, this method allows the change in earnings inequality to be decomposed into four components: changes in between-group gaps (δ_B), changes in within-group variation (δ_W), distribution effect (δ_D), and allocation effect (δ_A). Different from R^2 -based methods, this approach distinguishes the *dynamics* of inequality (i.e., analyzing the *change* in inequality) from the *statics* of inequality (i.e., analyzing the *level* of inequality). In a society, the principal factors that maintain the level of inequality do not always correspond to the major forces that drive the change in inequality. In fact, while geographic disparities remain to be the largest contributing factor to the level of inequality in China (Xie and Zhou 2014), we find that the rise of inequality in urban areas since the mid-1990s is not much driven by widening provincial disparities, but largely propelled by increasing returns to education and composition effects. An analysis of trends in R^2 , however, would not disentangle composition effects from inherent changes in between-group gaps or within-group variation. For example, Figure II.3 has shown a tremendous growth in the partial R^2 of education, yet this growth does not necessarily stem from an increase in returns to education. Without a

⁷ The same logic may be applied to speculate on the effects of interprovincial migration. Because of differences in pay and employment opportunities in manufacturing and service jobs, interprovincial migration in today's China is characterized by the flow of unskilled/semiskilled workers from inland, less developed regions to coastal, more developed regions. Given that these low-end workers would earn even less in their places of origin, interprovincial migration may have a mitigating effect on the rise of nationwide inequality. Undoubtedly, further research is needed to test this conjecture.

careful decomposition of the trend, we cannot separate the effect of changing returns to education from the effect of changing educational distribution. Similarly, without an explicit modeling of heteroscedasticity across employment sectors, we would conflate real changes in within-sector inequality with shifts in sectoral composition.

Substantively, this study provides new insights into the way economic inequality can be shaped by rapid socio-structural changes. For example, standard economic theory predicts that *ceteris paribus*, an educational expansion will cause a decline in returns to schooling owing to increased market competition. By this logic, if educational expansion produces a composition effect that drives up earning inequality, it may be offset or even outweighed by a drop in returns to education. This countervailing effect has been observed in both African and Latin American countries (Knight and Sabot 1983; World Bank 2011). My analyses, however, depict a different picture for China: returns to higher education have increased since the mid-1990s despite a growing supply of college-educated workers. As a result, these two forces have operated in the same direction toward a higher level of inequality. The impact of an educational expansion on inequality, therefore, may not always be predicted by a “partial equilibrium model;” instead, it can be shaped by an array of supply-side, demand-side, and non-market processes in a historical context.

While my analyses have broadly linked the growth in inequality to changes in earnings determinants, they are limited in revealing the complexity of micro-level processes. For example, although the observed increase in returns to education comports with the market transition theory, it is not necessarily due to market forces *per se*. First, if students with more (unobserved) family resources selectively obtained more education, the increase in estimated returns to education would reflect an increase in the compounded effects of schooling and family resources. Second,

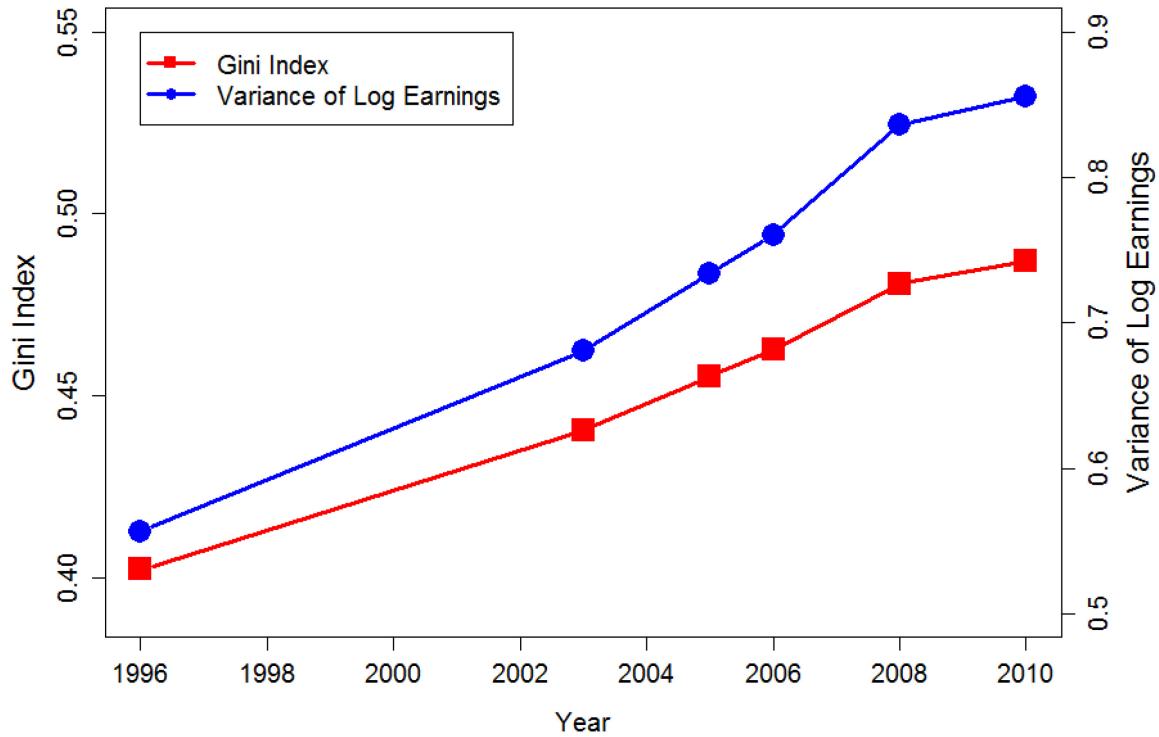
during the economic reform, state bureaucracies have increasingly emphasized educational credential in resource allocation, which may have also raised the observed returns to education. In fact, owing to state sponsorship, part-time adult colleges—which confer nearly a third of undergraduate diplomas in China—are much more likely to recruit mid-career cadres and state professionals than less privileged individuals (Lai 2014). If this effect had intensified over the study period, the observed increase in returns to college may have also been inflated.

The results of variance regressions show a markedly lower level of inequality in the state sector than in the private sector. This difference in residual inequality could also result from a wide range of sources. First, according to the human capital theory, residual inequality is often interpreted as reflecting the return to and the dispersion of unobserved skills. Compared with the state sector, the private sector is more directly exposed to market competition, under which variation in unmeasured skills is more likely to translate into different rates of pay. Also, workers in private firms may be more heterogeneous in unobserved skills than state sector employees (Wu and Xie 2003), which would lead to greater inequality in the private sector even if returns to unobserved skills were identical between the two sectors. Second, compared with the state sector, private firms may use more discriminatory practices in hiring and promotion, thus creating pay disparities even between workers with the same level of productivity. Third, as noted earlier, state-owned enterprises in China enjoy an array of institutional protections—such as government-granted monopoly and politically-favored bank loans—that help maintain a relatively low level of earnings dispersion among their employees. Finally, the difference in residual inequality between the two sectors could also stem from their differences in occupational and industrial structure. An assessment of these competing explanations, however, requires a large dataset that includes comprehensive measures of skills and detailed occupational

characteristics. I leave this challenge for future research. This study, though, highlights an important micro-macro nexus, that is, given that residual inequality is higher in the private sector than in the state sector, a decline in state sector employment will drive up earnings inequality in the aggregate.

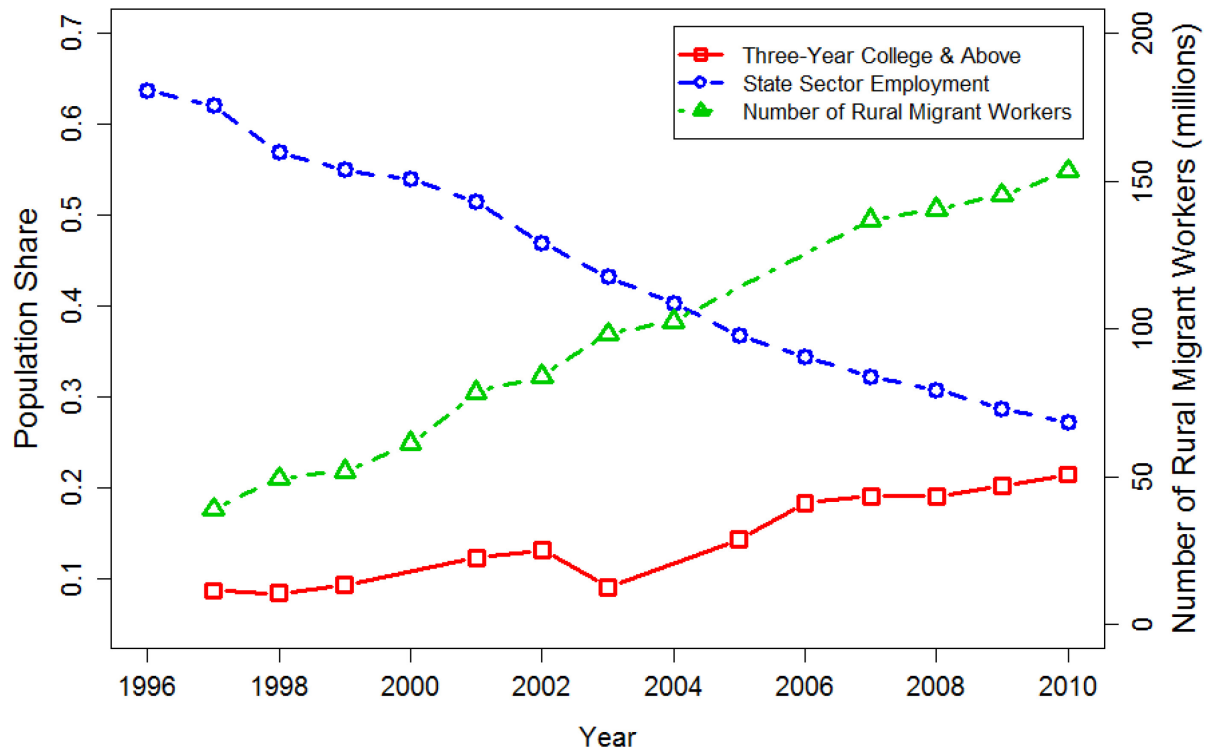
Earnings inequality in urban China has been on a steady rise since the early 1980s (Jansen and Wu 2012). Although the time span of my data does not allow an evaluation of the trends prior to 1996, previous research has shown that the growth in earnings inequality among urban workers up to the mid-1990s was chiefly propelled by widening regional gaps and increases in residual variation (Hauser and Xie 2005). Since then, however, the composition of the urban labor force has been significantly changed by college expansion, state sector downsizing, and a surge in rural-urban migration. By explicitly taking into account these institutional and demographic shifts, this article has demonstrated that the growth in earnings inequality over the past fifteen years stems mainly from increased returns to education and composition effects. In light of these results, I believe that the rise of inequality in urban China has been driven by different forces during different stages of the economic reform. Understanding such stage-dependent dynamics of earnings inequality greatly enriches our knowledge about the multifaceted processes of economic transformation in post-socialist China.

Figure II.1 Earnings Inequality among Working Population in Urban China, 1996-2010



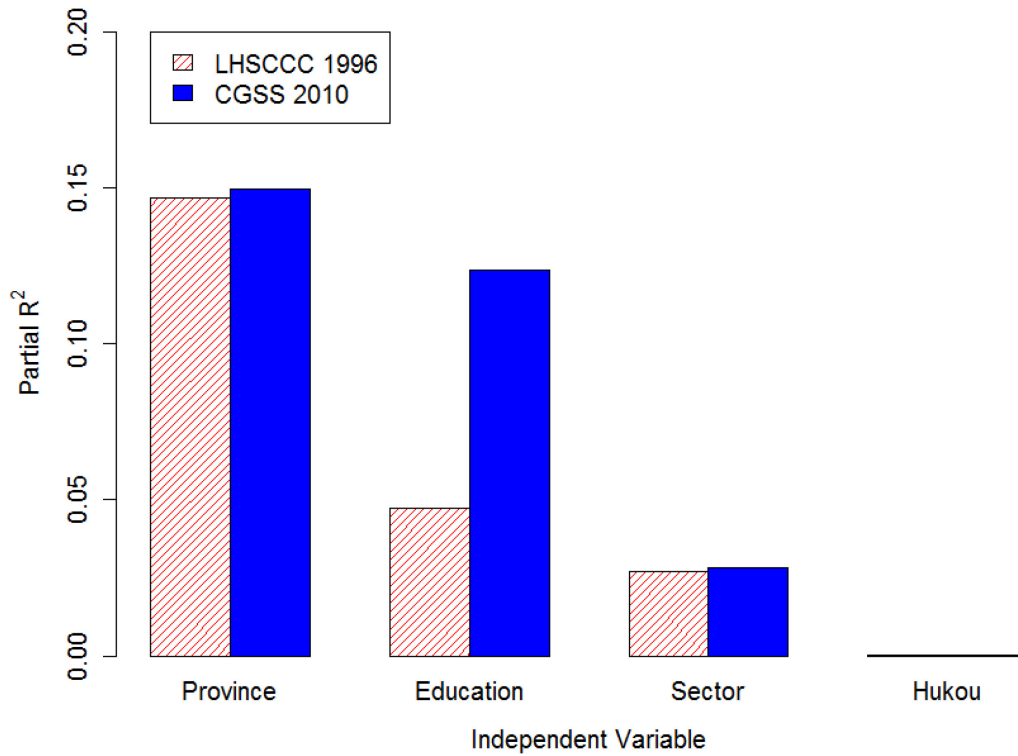
Note: Data are from the 1996 survey of “Life History and Social Changes in Contemporary China” (LHSCCC) and five waves of the Chinese General Social Survey (CGSS) from 2003 to 2010. Assuming the log-normality of earnings distribution, the Gini coefficients were calculated using the parametric formula $G = 2\Phi([V/2]^{0.5}) - 1$, where V is the variance of log earnings and Φ is the cumulative distribution function of standard normal distribution (see Allison [1978], 874).

Figure II.2 Compositional Changes in Urban China, 1996-2010



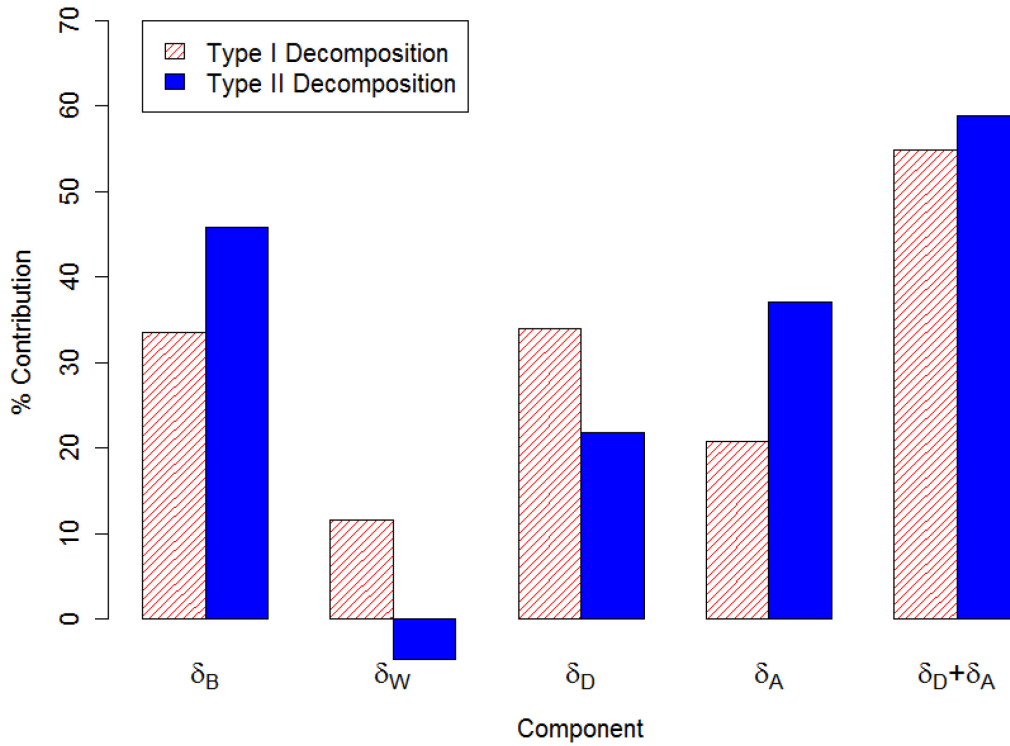
Note: The solid line shows the increasing share of college-educated people among the urban population at ages 6 and above (source: China Population and Employment Statistics Yearbook); the dashed line shows the declining share of workers in the state sector in urban China (source: China Labour Statistical Yearbook); the dot-dash line shows the increasing numbers of rural migrant workers in urban China (source: World Bank [2009] for years 1997-2007 and National Bureau of Statistics of China for years 2008-2010).

Figure II.3 Partial R²s for Province, Education, Sector, and Hukou Status in 1996 and 2010



Note: Besides these four key independent variables, all regression models also include sex, age, age squared, and party membership as covariates. For a variable K , partial $R^2 = \frac{R^2 - R_{-K}^2}{1 - R_{-K}^2}$, where R^2 is for the model that includes all independent variables, and R_{-K}^2 is for the model that includes all independent variables except K .

Figure II.4 Decompositions of the Rise in Earnings Inequality in Urban China, 1996-2010



Note: δ_B =changes in between-group earnings gaps, δ_W =changes in within-group earnings variation, δ_D =distribution effect (δ_D), δ_A =allocation effect (δ_A), $\delta_D + \delta_A$ =total composition effect.

Table II.1 Four-component Decomposition of the Change in Inequality

	Changes in Between-group/Explained Inequality ($\delta_B + \delta_D$)	Changes in Within-group/Residual Inequality ($\delta_W + \delta_A$)
Non-compositional Changes ($\delta_B + \delta_W$)	Changes in Between-group Earnings Gaps (δ_B)	Changes in Within-group Earnings Variation (δ_W)
Compositional Changes ($\delta_D + \delta_A$)	Distribution Effect (δ_D)	Allocation Effect (δ_A)

Table II.2 Evaluation of Competing Explanations

Competing Explanations	Mechanisms	Parameters to be Fixed at the 1996 Level
Widening Regional Disparities	Changes in Between-group Gaps	β_{region}
Increasing Returns to Education	Changes in Between-group Gaps	β_{edu}
Growing Residual Inequality	Changes in Within-group Variation	λ
Expansion of Tertiary Education	Distribution Effect	π_{edu}
Shrinkage of State Sector Employment	Allocation Effect	π_{sector}
Rural-to-urban Migration	Distribution Effect	π_{hukou}

Note: π_{edu} , π_{sector} and π_{hukou} denote the population distribution respectively by educational attainment, by sector of employment, and by *hukou* status. In this article, *hukou* status is used to distinguish between permanent urban residents and rural-urban migrants in urban China.

Table II.3 Descriptive Statistics of Population Share, Mean, and Variance of Log Earnings

		Population Share		Mean of Log Earnings		Variance of Log Earnings	
		1996	2010	1996	2010	1996	2010
Sex	Male	0.59	0.57	8.94	9.97	0.56	0.85
	Female	0.41	0.43	8.65	9.63	0.51	0.80
Age	20-29	0.27	0.19	8.82	9.92	0.64	0.73
	30-39	0.31	0.31	8.79	9.97	0.42	0.81
	40-49	0.28	0.34	8.84	9.77	0.53	0.79
	50-59	0.12	0.13	8.94	9.61	0.53	0.99
	60-69	0.03	0.03	8.49	9.10	1.33	1.19
Party Membership	Not Party-member	0.82	0.81	8.77	9.73	0.60	0.84
	Party-member	0.18	0.19	9.06	10.21	0.30	0.74
<i>Hukou</i> Status	Urban	0.88	0.73	8.83	9.92	0.53	0.87
	Rural	0.12	0.27	8.72	9.56	0.73	0.73
Educational Attainment	No Schooling	0.03	0.02	8.13	8.89	0.56	0.75
	Elementary School	0.14	0.14	8.64	9.28	0.82	0.77
	Junior High School	0.39	0.25	8.80	9.51	0.63	0.72
	Senior High School or Vocational High School	0.30	0.27	8.87	9.82	0.36	0.66
	Vocational College	0.08	0.18	9.02	10.16	0.32	0.51
	Four-year College or Above	0.05	0.14	9.25	10.61	0.21	0.64
Sector of Employment	State Sector	0.59	0.27	8.91	10.08	0.24	0.53
	Private Sector	0.23	0.51	8.81	9.71	0.59	0.80
	Self-employment	0.18	0.23	8.52	9.77	1.43	1.26

Note: Samples sizes are 2019 for LHSCCC 1996 and 3040 for CGSS 2010. All numbers in this table were adjusted using sampling weights.

Table II.4 Regression Results for Mean and Variance Functions in 1996 and 2010

Explanatory Variables		Mean Regression		Variance Regression	
		1996	2010	1996	2010
Intercept		8.690*** (0.158)	9.135*** (0.193)	-1.657*** (0.064)	-1.125*** (0.067)
Female		-0.222*** (0.025)	-0.307*** (0.026)		
Age		0.027*** (0.008)	0.065*** (0.009)		
Age ² /100		-0.025** (0.009)	-0.089*** (0.011)		
Party Membership		0.075* (0.031)	0.155*** (0.034)		
Rural <i>Hukou</i>		0.015 (0.050)	0.000 (0.034)		
Educational Attainment	No Schooling	-0.600*** (0.086)	-0.743*** (0.096)		
	Elementary School	-0.152*** (0.045)	-0.486*** (0.047)		
	Junior High School	-0.068* (0.029)	-0.252*** (0.037)		
	Senior High School or Vocational High School (Reference Group)				
	Vocational College	0.079† (0.043)	0.315*** (0.038)		
	Four-year College or Above	0.264*** (0.051)	0.608*** (0.042)		
State Sector (Reference Group)					
Sector of Employment	Private Sector	-0.112** (0.036)	-0.127*** (0.029)	0.794*** (0.121)	0.326*** (0.082)
	Self-employment	-0.358*** (0.061)	0.183*** (0.046)	1.843*** (0.134)	1.043*** (0.098)
Model R^2		0.240	0.415		

Note: †p<.1, *p<.05, **p<.01, ***p<.001 (two-tailed tests). Numbers in parentheses are standard errors. The mean models also control for province dummies, for which the coefficient estimates are not reported here. The mean and variance models were jointly fitted via maximum likelihood estimation (Western and Bloome 2009).

Table II.5 Adjusted Variances for Changes in Between-group Gaps and Within-group Variation

	2010	Change from 1996 to 2010	Percentage of Change Explained
Fitted Variance	0.839 (0.028)	0.304 (0.044)	
<i>Fixing Changes in</i>			
Regional Disparities (β_{region})	0.839 (0.034)	0.305 (0.041)	-0.2 (6.7)
Returns to Education (β_{edu})	0.701 (0.027)	0.167 (0.042)	45.2 (7.5)
All Between-group Gaps (β)	0.699 (0.030)	0.165 (0.038)	45.8 (7.9)
All Within-group Variation (λ)	0.853 (0.046)	0.319 (0.032)	-4.7 (16.1)

Note: Numbers in parentheses are bootstrap standard errors (250 replications). Bolded numbers identify the main driving forces of the rise in inequality.

Table II.6 Adjusted Variances for Changes in Population Composition

	2010	Change from 1996 to 2010	Percentage of Change Explained		
			Distribution Effect	Allocation Effect	Total
Fitted Variance	0.839 (0.028)	0.304 (0.044)			
<i>Fixing Compositional Changes in</i>					
<i>Hukou</i> Status (π_{hukou})	0.826 (0.030)	0.292 (0.044)	-1.5 (1.2)	5.6 (1.4)	4.1 (2.4)
Education (π_{edu})	0.802 (0.028)	0.268 (0.044)	21.9 (1.6)	-9.8 (1.5)	12.1 (2.6)
Sector (π_{sector})	0.780 (0.033)	0.246 (0.046)	-1.6 (2.9)	20.8 (2.7)	19.2 (5.0)
Education+ Sector ($\pi_{\text{edu,sector}}$)	0.711 (0.035)	0.177 (0.048)	21.0 (4.5)	20.8 (4.0)	41.9 (7.0)
All Explanatory Variables (\mathbf{X}, \mathbf{Z})	0.672 (0.026)	0.137 (0.037)	34.0 (5.9)	20.8 (4.5)	54.9 (7.6)

Note: Numbers in parentheses are bootstrap standard errors (250 replications). Bolded numbers identify the main driving forces of the rise in inequality.

CHAPTER III Market Transition, Industrialization, and Social Mobility Trends in Post-Revolution China

Sociologists have long sought to understand how political institutions shape social stratification. In particular, the transition from state socialism to market capitalism in China and the former Eastern Bloc countries has spurred a vast volume of research on the impacts of institutional changes on economic inequality. Prominent in this literature is Nee's (1989, 1991, 1996) market transition theory, which contends that the post-socialist transition is a process in which markets replace politics as the basic principle of resource allocation and thus predicts that human capital gradually replaces political loyalty as the main determinant of an individual's socioeconomic success. Empirical assessments of market transition theory abound. The dominant line of inquiry has revolved around the micro-level question of how economic payoffs of human capital relative to political capital have evolved over time (Bian and Logan 1996; Song and Xie 2014; Zhou 2000), differed by economic sector (Peng 1992; Rona-tas 1994; Wu and Xie 2003), or varied across regions at different stages of economic reform (Gerber 2002; Walder 2002; Xie and Hannum 1996). More recent research has also explored the implications of micro-level social determinants of income for macro-level inequality (Bandelj and Mahutga 2010; Hauser and Xie 2005; Zhou 2014), which has been growing rapidly in transitional economies (Heyns 2005; Xie and Zhou 2014).

So far, the market transition theory and its empirical assessments are almost exclusively concerned with inequalities of socioeconomic outcomes, such as income (e.g., Bian and Logan

1996), housing (e.g., Song and Xie 2014), and managerial positions (e.g., Walder, Li, and Treiman 2000), i.e., questions of intragenerational inequality. The consequences of market transition for inequality of opportunity—indicated by intergenerational social mobility—remain underexplored. In a pioneering study, Gerber and Hout (2004) report that the net association between class origins and class destinations strengthened following the collapse of communism in Russia in the 1990s, suggesting that state socialism might have been conducive to equality of opportunity in the former Soviet Union. Gerber and Hout’s conclusion prompts the question of whether social fluidity declines in general with a society transitioning from state socialism to a market economy. To answer this question, we need to understand trends in intergenerational mobility in other societies that have undergone similar transitions. A prime candidate for addressing this question is China.

The question of trends in intergenerational mobility has attracted sociological attention for a much longer period than the market transition debate. In particular, a large literature in comparative stratification has been devoted to understanding the effects of economic development on intergenerational social mobility (Ganzeboom, Treiman, and Ultee 1991). Two prominent hypotheses have emerged in this literature. First, the “thesis of industrialism” predicts that the more industrialized a society is, the higher the degree of social fluidity (Treiman 1970: 221). Second, in what is known as the FJH hypothesis, Featherman, Jones, and Hauser (1975) argue that while there may be an initial effect of economic development, improvement in social mobility is limited when a society becomes sufficiently industrialized. While the bulk of empirical work in the past has been consistent with the FJH hypothesis (Erikson and Goldthorpe 1992; Grusky and Hauser 1984), more sensitive tests of trends in the form of the “Unidiff” model (Xie 1992) suggest that social fluidity has increased in many industrialized nations over

the 20th century, albeit slowly (Breen and Jonsson 2007; Breen and Luijkx 2004; Vallet 2001). However, these two hypotheses have been challenged in a recent article by two economists (Long and Ferrie 2013). Using historical census data and the 1973 Occupational Changes in a Generation (OCG II) survey, Long and Ferrie find that intergenerational occupational mobility in the U.S. was much higher in the late-19th than in the mid-20th century. Considering that rapid industrialization in the U.S. took place between 1860 and 1930 (Xie and Killewald 2013), Long and Ferrie's finding contradicts both of the two hypotheses by suggesting that social fluidity in a major modern society declined over its course of industrialization. Controversial as it is, Long and Ferrie's study poses serious challenges to the two prominent hypotheses in sociology about the effect of industrialization on social mobility.

In the current literature evaluating the industrialism thesis and the FJH hypothesis, industrialization is construed as the level of industrial development at a given time point for a given society, undifferentiated for the parents' versus children's generations. In other words, industrialization is treated as a state, not a process. While this approach is reasonable for comparisons of societies undergoing industrialization at similar paces, it is inadequate if there is a substantial variation in the pace of industrialization across societies being compared. A rapid pace of industrialization, net of the industrialization level, may play a direct role in promoting social fluidity. Indeed, a number of national studies have suggested that rapidly industrializing societies, such as Israel and Korea in the 1960s and 1970s, seem to exhibit relatively weak class boundaries, especially between agricultural and nonagricultural classes (e.g., Goldthorpe, Yaish, and Kraus 1997; Ishida, Goldthorpe, and Erikson 1991; Park 2003; Torche 2005). These pieces of evidence, however, are at best fragmentary at the present. To our knowledge, no systematic

effort has been made to explore the theoretical implications of the pace of industrialization for social mobility.

China's recent history provides a unique opportunity for better understanding the impacts of market transition and rapid industrialization on intergenerational social mobility, as the country has experienced striking industrial expansion as well as the demise of socialism since its economic reform began in 1978. This article represents our effort to exploit this opportunity. Using data from six waves of comparative, nationally representative surveys from 1996 to 2012, we analyze trends in intergenerational class mobility among Chinese men and women born between 1936 and 1981. We use log-linear analysis to carefully examine patterns of class fluidity net of changes in the marginal distribution of the Chinese class structure. In particular, we model three distinct dimensions of class fluidity—status hierarchy, class immobility, and affinity—and trace them across four birth cohorts. Besides the roles of marketization and industrialization, we also pay close attention to the influences of a peculiarly Chinese social institution—the household registration (*hukou*) system—that puts agricultural workers at a structural disadvantage by preventing them from migrating to and settling down permanently in cities (Wu and Treiman 2004).

We further interpret temporal trends in social fluidity in China within an international context by comparing patterns of mobility in different Chinese cohorts with those in 12 advanced industrial countries analyzed in Erickson and Goldthorpe's (1992) project, *Comparative Analysis of Social Mobility in Industrial Nations* (henceforth CASMIN). Our own comparative analysis involves measuring the magnitudes of social fluidity or rigidity in post-revolution China relative to those in more developed countries. Capitalizing on temporal trends in China as well as cross-

national variation, we aim to understand how patterns of intergenerational social mobility may be affected not only by the level, but also by the pace, of industrialization.

Theoretical and Methodological Issues

State Socialism, Market Transition, and Class Stratification

Class theorists have long speculated about the influences of political institutions on social stratification. As both Parkin (1971) and Giddens (1973) suggest, compared with liberal capitalist societies, state socialist regimes may exhibit less class-based stratification due to the absence of private property, less differentiated reward systems, and more egalitarian social policies (see also Szelényi 1998). This argument may well have been applicable to socialist China. First, the socialist state policies carried out immediately following the founding of the People's Republic of China in 1949 eliminated virtually all forms of private property and effectively reduced the "bourgeoisie class" to a group of peddlers, shopkeepers, and self-employed artisans and handicraft workers, which according to our data altogether constituted less than 2% of the entire labor force. The abolition of inheritable property removed material obstacles to upward mobility for the poor as well as financial protections against downward mobility for the rich. Hence, the economic foundation underlying the class structure may have played a much weaker role in class reproduction in socialist China than in the West.

Second, up until the end of 1980s, most urban workers in China were employed by the state, which imposed a rigid wage grade system that deliberately suppressed income inequality, both within and between occupational classes. Thus, children of different class origins had more equal material resources for occupational attainment than would have been the case in a highly unequal society. Relatively low income inequality, moreover, reduced the economic incentives

for elites to transmit their social advantages to their offspring. Class mobility, in other words, was a game of low stakes.

Finally, in the pre-reform era, especially during the Great Leap Forward (1958–1960) and the Cultural Revolution (1966–1976), the Chinese government vigorously pursued a set of egalitarian educational policies that favored the offspring of peasants, workers, and soldiers, including the abolition of tuition fees, dramatic expansions of primary and secondary education in the countryside, and an emphasis on political criteria rather than academic ability for admission to universities (Meisner 1999: 362-63). As a result, educational opportunities were greatly enhanced for socially disadvantaged groups, such as rural youth, women, and the urban poor (Hannum and Xie 1994; Zhou, Moen, and Tuma 1998). Since a good education, particularly at the post-secondary level, could lead to a managerial or professional job in the state sector, it is reasonable to suppose that social mobility, particularly long-range upward mobility, should have been higher under Chinese state socialism than in a liberal market economy.

Since 1978, the economic reform in China has dismantled the old system of state planning and embraced markets as the guiding principle of resource allocation. What is the implication of the market-oriented reforms for intergenerational mobility? Earlier research has shown declines in class fluidity following the collapse of state socialism in Russia (Gerber and Hout 2004) and Hungary (Robert and Bukodi 2004). Given the experiences in Eastern Europe, there are good reasons to conjecture that the process of market transition may have also led to a less open class structure in China (Bian 2002). First, the emerging private sector has provided abundant opportunities for administrative elites to accumulate wealth through their political influence and social networks (Bian and Logan 1996; Rona-tas 1994). For instance, many government officials have successfully turned themselves into private entrepreneurs or become

patrons of private businesses formally owned by their relatives or friends (Meisner 1999: 475-77). Since economic resources are readily inheritable, the conversion of political power into personal wealth has greatly facilitated the intergenerational reproduction of socioeconomic status, if not of occupational titles.

Moreover, during the reform era, the Chinese government deregulated the state sector and its rigid reward system. Wage differentials increased substantially between professionals and regular workers, and among workers with differing skills (Zhou 2000). Due to the deregulation of wages as well as the expansion of the private sector, income inequality has soared in China over the past three decades (see Xie and Zhou 2014). Hence, the upper class now has both more resources and stronger motivation to pass their advantages on to their children. In addition, the populist educational policies in favor of the rural population during the Maoist era have largely been abandoned, and in their place is a more selective system of recruitment. Wu (2010) shows that during the 1990s, the effect of family background on educational attainment increased, and the rural-urban gap in the likelihood of transition to senior high school widened. Thus, for children of underprivileged families, especially those of rural origin, the prospect of long-range upward mobility may have become much slimmer than in the past. In light of these processes, we would expect that *the link between class origin and class destination has tightened during China's post-socialist transition, making it difficult for intergenerational mobility to occur along the socioeconomic hierarchy.*

Industrialism, Rapid Industrialization, and Social Mobility

One of the earliest explanations that stratification scholars have proposed to account for trends in social mobility highlights the role of industrialization. The “thesis of industrialism,” in particular, states that industrial development should promote equality of opportunity because it entails a

process of economic rationalization that will shift the emphasis away from ascription to achievement in the allocation of social positions (Treiman 1970; see also Blau and Duncan 1967: chapter 12). As an integral part of industrialization, the argument goes, the spread of public education and the expansion of mass communications serve to reduce the economic and cultural barriers to movement between classes, and urbanization and greater geographic mobility tend to loosen ties of kinship and thus the influence of family background on occupational attainment.

By definition, industrialization fundamentally alters the prevailing occupational structure and thus necessarily changes the distribution of social classes from the parental generation to the child generation (Duncan 1966; Sobel, Hout, and Duncan 1985). Hence, industrialization necessitates an increase in structural mobility. The focal quantity of interest in the comparative mobility literature, however, is social fluidity, i.e., relative social mobility net of overall changes in the class structure across generations (Featherman and Hauser 1978; Goodman 1969). Some national studies find upward trends in social fluidity over time (e.g., Breen 2004; Featherman and Hauser 1978; Ganzeboom, Luijkx, and Treiman 1989; Hout 1988; Wong and Hauser 1992). However, many cross-national studies (e.g., Erikson and Goldthorpe 1992; Grusky and Hauser 1984; Wong 1990) have rejected the thesis of industrialism in support of a competing hypothesis proposed by Featherman, Jones, and Hauser (1975). In what is known as the FJH hypothesis, it is argued that while there may be an initial effect of economic development on mobility, relative mobility is largely stable and cross-nationally similar once a certain level of industrialization is reached.⁸

⁸ An antecedent of the FJH hypothesis, which did not distinguish structural mobility from social fluidity, was advanced by Lipset and Zetterberg (1959: 13).

In both the thesis of industrialism and the FJH hypothesis, the notion of industrialization is construed as the level of industrial development that is roughly applicable to both generations in a mobility regime. This is a reasonable assumption when industrialization has run its course, as is the case for advanced industrial societies such as those in contemporary Western Europe and North America. For a rapidly industrializing society such as post-revolution China, however, the employment structure is likely to undergo dramatic changes from one generation to the next. Furthermore, the pace of industrialization may change greatly over time. In fact, the percentage of workers not in agriculture—a common indicator of industrialization—increased slowly in the first three decades of the People’s Republic, from 16% in 1952 to 31% in 1980; but by 2011, this figure had soared to 65% (National Bureau of Statistics of China 2012). In this paper, we adopt a convenient measure of the pace of industrialization as the generation gap in the proportion of agricultural employment, as a faster pace of industrialization is associated with a larger generation gap in the proportion of agricultural employment. We will show later in this paper that the generation gap in the proportion of agricultural employment has differed greatly across cohorts in post-revolution China.

We contend that the *pace* of industrialization—net of the level of industrialization—may exert a distinct influence on occupational mobility, not only through shifts in occupational structure per se, but also through its effects on the relative chances of mobility into and out of the agricultural sector. Indeed, there is ample empirical evidence showing that the boundary between the agricultural and nonagricultural sectors tends to be particularly permeable in a rapidly industrializing society. For example, drawing on historical census data, Guest, Landale, and McCann (1989) discovered that, relative to the mid-20th century United States, barriers to entering farming were much weaker in the late-19th century U.S., when the country experienced

massive industrial expansion. This is in fact the primary cause for Long and Ferrie's (2013) finding that social mobility declined in the U.S. over the first half of the 20th century (Hout and Guest 2013; Xie and Killewald 2013). In the CASMIN project, Erikson and Goldthorpe (1992) also found that, compared with Western European countries, intergenerational movement between the farming and nonfarming sectors was more prevalent in Hungary and Japan, two countries with accelerated paces of industrialization in the post-war years. There is also evidence that sectoral barriers are relatively weak in newly and rapidly industrializing countries, such as Israel (Goldthorpe et al. 1997), Korea (Park 2003), and Chile (Torche 2005). A common explanation, as alluded to by some of these authors, is that the process of industrialization tends to create a large volume of part-time farmers, or “semi-proletarians,” who take jobs in the industry sector but retain ties to the land either themselves or through their families, thus effectively straddling the agricultural and industrial sectors (Erikson and Goldthorpe 1992: 153-154).

China has been on a path of rapid industrialization since the economic reform began in 1978. Hundreds of millions of rural-urban migrant workers leave their parents and children in the countryside and supplement family income through various kinds of nonfarming work. More importantly, due to the household registration system (see the next section), rural migrant workers in China are denied legal urban status and the right to permanent migration to cities. The offspring of migrant workers in China, as a result, are highly vulnerable to downward mobility, i.e., becoming peasants themselves. Therefore, we would expect that net mobility between farming and nonfarming occupations has increased during the recent years of rapid industrialization and massive rural-urban migration. In our analysis, we will also draw on cross-

national data to assess the hypothesis that *a faster pace of industrialization is associated with greater exchange mobility between the agricultural and nonagricultural sectors.*

The Hukou System and Patterns of Class Mobility in China

In concluding the CASMIN project, Erikson and Goldthorpe (1992) argued that cross-national differences in patterns of social fluidity were largely due to country-specific historical and political circumstances rather than to generic factors such as the degree of economic development. In China, an idiosyncratic factor shaping the structure of social mobility is the household registration (*hukou*) system. Established in the 1950s, the *hukou* system requires that all households be registered in the locales of their residence for the government to tightly control population mobility, especially between rural and urban areas (Wu and Treiman 2004). Further, children inherit their parents' *hukou* status.⁹

The vast majority of rural Chinese, as a result, are tied to their home villages, with little prospect of upward mobility. For this reason, a major dimension of social inequality in China has been the divide between the rural and urban populations (Xie and Zhou 2014). Still, the government has policies that allow a rural person to acquire an urban *hukou* under special circumstances, among which the most typical is enrollment in an institution of tertiary or technical education. Given the urban population's structural advantages over the rural population, incentives through this channel of mobility for rural Chinese are very high (Chan and Zhang 1999; Wu and Treiman 2004). Since a tertiary or technical education almost surely confers an administrative or professional job, a large proportion of those who manage to change their *hukou* status end up in relatively high-status positions. Thus we would expect that in China,

⁹ In the case when one of the parents has an urban *hukou* while the other has a rural *hukou*, the child usually inherits the mother's *hukou* (Chan and Zhang 1999).

those few individuals who have successfully moved out of agriculture intergenerationally will be well represented in the upper echelon of the socioeconomic hierarchy.

Interestingly, previous research also reveals that reverse mobility from the professional and managerial class to the agriculture class has also been particularly common in China (Cheng and Dai 1995; Wu and Treiman 2007). To explain this phenomenon, Cheng and Dai (1995) pointed to the policy of rustication during the Maoist era: two waves of “send-down” campaigns before and during the Cultural Revolution forced tens of millions of urban youths, especially the offspring of urban intellectuals and bureaucrats, to go to the countryside and labor in the fields. Wu and Treiman (2007) nonetheless discounted this explanation by pointing out that most urban youths who were sent down had returned to the cities by the 1980s. Instead, they suggest that the long-range downward mobility back to agriculture is also a unique product of the *hukou* system. Specifically, children of rural cadres are likely to become peasants themselves because opportunities to obtain nonagricultural work, either white collar or blue collar, are scarce in the countryside. In other words, the *hukou* system, combined with a rural occupational structure composed mostly of a vast peasantry and a small group of village cadres, has led to disproportionate amounts of exchange mobility between the agricultural and the professional/managerial classes.

The *hukou* system may have also produced a structural affinity between agriculture and self-employment. While private property ownership, as noted earlier, was officially outlawed in pre-reform China, this restriction on private property was effectively enforced mostly in urban areas, where the government had the economic power to employ all urban workers and the administrative capacity to disallow private businesses. As a result, a small number of rural Chinese were still engaged in self-employment, such as peddlers, petty shopkeepers, and self-

employed artisans. Because they were mainly confined to rural areas and had rural *hukou*, their offspring, if occupationally mobile, would be more likely to enter farming than any other occupation. The affinity between these two groups may have become even stronger in the reform era. As noted by Nee (1989), although the economic reform encouraged private entrepreneurship from the beginning, it was the lower tiers of the social hierarchy who initially took advantage of the market opportunities. In rural areas, following the breakup of agricultural collectives and the establishment of the household responsibility system, a large number of surplus laborers that were freed from the production teams began to start their own businesses. In urban areas, both party cadres and regular state workers initially had too high a stake in the existing system to plunge into the precarious private sector. As a result, the vast majority of private entrepreneurs in the early phase of the economic reform also came from marginalized social groups, particularly rural-urban migrants (Wu and Xie 2003; Wu 2006). However, because the core of the *hukou* system has been left largely intact since the market reform, the offspring of these early entrepreneurs faced little chance of entering the formal urban economy, and many ended up becoming peasants again, constituting a pattern of reverse mobility from self-employment to farming.

From the above discussion, we would expect that due to the institutional segregation of the rural and urban populations, *class mobility in China has been shaped by disproportionate flows between farming and the managerial/professional class, and between farming and self-employment*. In the analysis that follows, we incorporate these two patterns of affinity into models of class fluidity and its trends. Moreover, we use cross-national data to test whether these affinities are truly unique to contemporary China or shared by other countries as part of a general mobility regime.

Social Mobility as a Multidimensional Process

The earlier discussion suggests that trends in social fluidity in China's recent history have been influenced by two opposing social forces: on the one hand, social fluidity may have declined due to the demise of state socialism; on the other hand, social fluidity may have been facilitated by rapid industrial expansion. It seems that these two effects may have offset each other to a degree at which neither can be empirically detected. This is not necessarily the case, however, because social mobility is a multidimensional process and can be understood as such (Hout 1984; Wong 1992). It is true that intergenerational data, including those analyzed in this paper, are typically two-way cross-classifications (F_{ij}) of social origin, i.e., parental class/occupation status ($i = 1, \dots, I$), by social destination, i.e., children's class/occupation status ($j = 1, \dots, J$). Typically, $I = J$ if the same measurement is applied for both social origin and destination. However, because there are multiple categories in the measurement of origin and destination (i.e., $I = J > 2$), multiple latent dimensions of association between origin and destination can be exploited in such two-way tables (Goodman 1979; Hauser 1980).

Our earlier discussion suggests that market transition and industrialization affect social mobility differently, not only in the overall direction of reducing versus increasing social fluidity but also in weakening or enhancing specific flows of social mobility: While market transition reduces social fluidity by making intergenerational mobility along status hierarchy more difficult, rapid industrialization promotes social fluidity by weakening the barrier between the farming and nonfarming sectors. As we will show, these two effects can be separately modeled in a two-way mobility table via log-linear analysis.

Of course, this is not the first study to investigate trends in social mobility in China. Using data collected from six selected provinces, Cheng and Dai (1995) showed that relative

chances of mobility between different class origins had been largely stable throughout China's state socialist era. More recently, drawing on data from two nationally representative surveys, Chen (2013) also found little evidence for either an upward or a downward trend in social fluidity during the reform era. Neither of these studies, however, attended to the multiple dimensions of class fluidity and changes therein; in fact, their assessments of temporal trends were both based on the Unidiff model (Xie 1992), which hinges on the strong assumption that different dimensions of class fluidity, such as status hierarchy and sectoral barrier, would change in exact proportion to one another over time. If this assumption does not hold true, it may lead researchers to overlook the theoretically important changes we discussed earlier. Our study relaxes this assumption by examining how the different dimensions of class fluidity have evolved separately over time. As we will show, recent trends in class fluidity are simultaneously characterized by a strengthened status hierarchy and a weakened sectoral barrier—a finding that has eluded previous studies that inadequately encapsulated multidimensional changes in a single indicator.

Gender and Trends in Social Mobility

Many national studies on social mobility trends have relied on male samples only (e.g., Featherman and Hauser 1978 for the United States; Goldthorpe et al. 1997 for Israel; Park 2003 for Korea; Torche 2005 for Chile), primarily because female labor force participation may have been differentially selective over time in those societies. When women's labor force participation rate is low, as was the case in many western countries, women of upper class origins are more likely to stay out of the labor force than women of lower class origins because the former are more likely to be married to husbands with high incomes (Fligstein and Wolf 1978; Hauser, Featherman, and Hogan 1977). In the past four decades in western countries such as the U.S.,

women's labor force participation has significantly increased, along with their educational attainment, commitment to career jobs, and financial contributions to families (Bianchi, Robinson, and Milke 2006; Blau, Brinton, and Grusky 2006; DiPrete and Buchmann 2013). If women's non-participation in the labor market is selective, it is evident that the strength of this selection has changed over the period when women's labor force participation has significantly increased. Hence, it would be difficult to disentangle real changes in social fluidity among women from changes in the selectivity of their labor force participation. As a result, it is difficult to compare trends in intergenerational mobility for men with those for women.

However, leaving women out of analysis is a convenience, but not a solution. Ideally, we would want to track trends in intergenerational mobility for both men and women, as all relevant theories on trends in intergenerational social mobility, as we discussed earlier, are equally applicable for both men and women. We thus expect similar trends by gender. For the present study, if trends in class fluidity in China differed significantly between men and women, it would severely undermine our theoretical interpretation of the findings at the societal level. Fortunately, the problem of selectivity for women's labor force participation is relatively minor for post-revolution China, where female labor force participation has been consistently high compared with other societies (Bauer et al. 1992). In the United States, for example, the labor force participation rate among women at ages 25–54 increased from 45% in 1965 to 75% in 2005, whereas the same indicator for China stayed around 85% throughout this period (Bauer et al. 1992; International Labour Organization 2014; Mosisa and Hipple 2006). Therefore, in the following analysis, we report results for both men and women and discuss gender differences when they appear.

Data and Measures

Data for this study come from six nationally representative sample surveys: the 1996 survey of Life Histories and Social Change in Contemporary China (henceforth LHSCCC 1996) and five waves of Chinese General Social Survey (henceforth CGSS) conducted in 2005, 2006, 2008, 2010, and 2012. These surveys are highly comparable from design to implementation (Bian and Li 2012; Treiman and Walder 1998). First, all these surveys employed a standard multistage sampling design under which one adult was randomly selected from each sampled household. Moreover, in both LHSCCC 1996 and CGSS, the fieldwork was implemented by the same organization: the Department of Sociology at Renmin University of China. In this study, the six samples were pooled to form a single data file by extracting information on gender, age, current job, the father's job at the time when the respondent was 14 (18 for CGSS 2006) years old, and sampling weights. To track trends over cohorts from the repeated cross-sectional data, we assume that a typical worker would hold a steady job that is likely to last for lifetime. This assumption is likely to hold true for earlier cohorts but is more problematic for recent cohorts. Earlier research shows that intragenerational job mobility in post-reform China is high mostly among young workers, relatively low by international standards, and largely between jobs with similar characteristics (i.e., within the same class) (Whyte and Parish 1985; Zhou, Tuma, and Moen 1997). To be conservative, we construct our measure of social destination from one's job at the age of 30 or older. Operationally, we restrict the sample to respondents who were actively in the labor force and between ages 31 and 64 at the time of the survey. In doing so, we aim to minimize life cycle effects that may confound observed trends across cohorts. We also exclude respondents who were born before 1936 because our analytical focus is on the post-revolution

period of the People's Republic of China.¹⁰ After the elimination of a small fraction of cases with missing variables (less than 10%), our final sample consists of 16,045 men and 15,763 women.

To facilitate international comparisons, we adopt the widely used EGP class scheme to measure social origin and destination (Erikson, Goldthorpe, and Portocarero 1979). Specifically, we code occupations into a six-category version of the EGP scheme: the service class (I+II), routine non-manual workers (III), the petty bourgeoisie (IVa+b), skilled manual workers (V+VI), unskilled manual workers (VIIa), and farmers and agricultural laborers (IVc+VIIb). Table III.1 shows its relationship with the original 10-category version proposed by Erikson et al. (1979). In fact, the only difference between our six-category version and the seven-category version adopted in the CASMIN project and most subsequent comparative studies is that self-employed farmers and agricultural laborers are combined in our classification. The distinction between these two groups is largely irrelevant in China because private ownership of land is strictly prohibited in both the socialist and post-socialist periods. Even in a fully capitalist society, it is sometimes difficult to distinguish between the two groups, given that children of self-employed farmers who work on their family farms are often classified as agricultural laborers before they inherit the land (Ishida et al. 1991). In our comparative analysis, we collapse all 7×7 tables used in the CASMIN project into their 6×6 versions.¹¹

¹⁰ For a person born before 1936, his/her social origin—defined by the father's occupation when he/she was 14—would be situated in an entirely different political regime.

¹¹ We also ran a global test of the four aggregations by fitting the independence model to the full 10×10 table and the collapsed 6×6 table, respectively (Goodman 1981). Although statistically significant, the difference in G^2 covers only 13.7% of the total row-column association (623/4563=13.7%). In other words, more than 85% of the association between social origin and destination is conveyed by the six-class version of the EGP scheme.

According to our sample restriction criteria, our data consist of individuals who were born between 1936 and 1981. To examine temporal trends, we divide them into four birth cohorts: 1936–1951, 1952–1961, 1962–1971, and 1972–1981. These four birth cohorts roughly correspond to four cohorts who entered the labor force—around 18 years of age—during the 1960s, 1970s, 1980s, and 1990s, respectively. Although the market transition in China started as early as 1978, it was highly incremental and did not gather much momentum until 1992, when Deng Xiaoping made his famous southern tour. Thus, we may label the third cohort (1962–1971) as the “early reform cohort” and the fourth as the “late reform cohort.” With the six-class measure of social origin and destination and the definition of four cohorts, the analytical sample can be organized as a $6 \times 6 \times 4$ contingency table.

Methods and Analysis Plan

In this study, we model multiple dimensions of class fluidity in intergenerational mobility tables, including status hierarchy, class immobility, and affinity, and allow them to evolve independently across cohorts. To achieve this goal, we first consider the “core model of social fluidity” advocated by Erikson and Goldthorpe (1987, 1992). Initially derived to fit data from England and France, the core model purports to depict a common pattern of class fluidity among all advanced industrial societies. It uses eight “design matrices” to characterize four types of effects—hierarchy, inheritance, sector, and affinity—that enhance or reduce mobility between specific classes. In particular, the hierarchy effects gauge the impact of status distances on the degree of mobility. The larger the hierarchy effects, the greater the level of vertical stratification. The inheritance effects capture the tendency of immobility and its variation across different classes. The sector effects reflect the difficulty of moving between the agricultural and nonagricultural sectors. Finally, the affinity effects are used to capture disproportionate amounts

of movement between specific classes that cannot be explained by the effects of hierarchy, inheritance, and sector. However, the core model was originally formulated to fit the 7×7 mobility tables that separate out self-employed farmers from agricultural laborers. To adapt the core model to the six-class version of the EGP scheme, we convert the eight 7×7 design matrices to 6×6 matrices by removing the row and the column representing self-employed farmers, a category that does not formally exist in China. In this adaptation of the core model, the sector effect becomes redundant because it corresponds exactly to the inverse of the inheritance effect for the farming class.

The core model of social fluidity, however, has been criticized for a number of its drawbacks (see Hout and Hauser 1992). For instance, it uses only two crossing parameters to represent status differences among seven classes, thus inadequately representing the fine gradations along the socioeconomic hierarchy. Moreover, the affinity effects seem to be deliberately chosen to fit the English and French data and may not reflect historical and political circumstances in other countries. For these reasons, we adopt a hybrid model that uses a linear-by-linear specification to characterize the status hierarchy, six diagonal terms to identify class-specific immobility, and four Chinese-specific affinity parameters to capture disproportionate flows between farmers and the service class and between farmers and the petty bourgeoisie. The model can be expressed by equation (1).

$$\log F_{ij} = \mu + \mu_i^R + \mu_j^C + \theta X_i^R X_j^C + \delta_i D_{ij} + \sum_{p=1}^4 \alpha_p Z_{ij}^p \quad (1)$$

Here, the first three terms are used to saturate the row and column marginal distributions, and the parameters θ , δ_i , and α_p represent the effects of hierarchy ($X_i^R X_j^C$), immobility (D_{ij}), and affinity (Z_{ij}^p), respectively. In the linear-by-linear specification, the row scores X_i^R and columns scores X_j^C can either be externally derived or internally estimated. In the latter case, the model is an

extension of the RC (II) model (Goodman 1979). Were the affinity parameters absent, equation (1) would correspond to a quasi-linear-by-linear model or quasi-RC (II) model.

In the following analysis, we first select a model that best captures the general patterns of class fluidity in China. We then examine trends in fluidity by allowing specific parameters of the selected model to vary across cohorts. In both steps, we use the Bayesian Information Criterion (BIC) to compare the fit of alternative models (Raftery 1995). The model with the lowest BIC is preferred. Furthermore, we put China in a comparative perspective by examining cross-national variations in different dimensions of class fluidity. Finally, we conduct two sets of sensitivity analyses to test whether the observed trends across cohorts are contaminated by age or period effects.

Results

Trends in Class Structure and Absolute Mobility Rates

Given China's vast social and economic transformation over the past few decades, it is instructive to examine trends in class structure and absolute mobility rates before moving on to the analysis of class fluidity. Figure III.1 shows the changes in the marginal distribution of class destinations across the four birth cohorts. Several trends are worth noting. First, although women were more likely to be engaged in farming than men, the proportion of agricultural employment declined sharply for both sexes. Industrialization gained more momentum in recent decades, as reflected in the steeper slope of decline from the third to the last cohort than in earlier successive cohorts. Second, for both men and women, the proportion of petty bourgeoisie rose steadily, reflecting the gradual expansion of markets since the late 1970s as well as the fact that younger cohorts were more likely to work in non-state sectors than older cohorts. Finally, the proportion

of the service class increased considerably from the third cohort to the last cohort, reflecting the latest technological changes and rapid growth in managerial and professional jobs.

Figure III.2 shows trends in absolute mobility rates, with rates of upward mobility, downward mobility, and immobility represented respectively by squares, circles, and triangles. Here we treat the six classes as ordered in the sequence as they appear in Table III.1. Thus, the rate of upward/downward mobility corresponds to the proportion of workers who were in a higher/lower class position than their fathers, and the rate of immobility corresponds to the proportion of workers who were in the same class as their fathers. We can see that from the second cohort on, the rate of upward mobility increased substantially for both men and women. Yet the rise in upward mobility came from a decline in class immobility rather than in downward mobility. In fact, rates of downward mobility have been fairly stable over time, ranging from 10% to 15% for both sexes. Given the rapid decline in farming, as shown in Figure III.1, we may infer that both rising upward mobility rates and declining class immobility rates resulted mainly from industrialization, which moved a large proportion of the peasantry into the industrial sector. To test this conjecture, we excluded the farm sector from the mobility tables and recalculated the three rates for the 5×5 sub-tables. The results, represented in dashed lines, confirm our conjecture. When the farm sector is excluded, both the rise in upward mobility and the decline in class immobility disappear, and all three rates exhibit no more than trendless fluctuations. Indeed, the nonagricultural labor force is about equally divided into the three groups of upwardly mobile, downwardly mobile, and immobile in each cohort for both men and women.

Patterns of Class Fluidity

We now use log-linear analysis to assess the net effects of origin on destination, i.e., class fluidity. In the first step, we select a model that best depicts general patterns of fluidity in all

cohorts. In other words, the parameters representing origin-destination association are assumed to be constant across cohorts. The goodness-of-fit statistics for competing models are reported in the upper panel of Table III.2. Let us first consider two baseline models. First, the conditional independence model (model 1) saturates the two-way marginal distributions of origin-by-cohort and destination-by-cohort, but it stipulates that origins and destinations are independent within each cohort. The large G^2 and BIC lead us to simply reject this naive model. The model of constant social fluidity (model 2) specifies that the degree of class fluidity is invariant across cohorts but otherwise does not constrain the form of association between origin and destination. It greatly improves the fit to the data, capturing all but about 3% of the origin-destination association (measured by G^2) for both men and women. However, by saturating the row-column interaction, the model of constant social fluidity does not explicitly “model” patterns of intergenerational transmission. Yet we use it a benchmark against which more restricted models of cohort-invariant association are evaluated.

The core model of social fluidity (model 3) fits the data reasonably well, explaining most of the origin-destination association with only seven parameters ($G^2=385$ for men; 588.8 for women). But in terms of the BIC, it compares unfavorably with the model of constant social fluidity. As noted earlier, one of the drawbacks of the core model is that the affinity terms were based on peculiarities of specific Western societies, especially England and France. We next modify the core model to suit the Chinese case by replacing the original affinity terms with the four affinity terms that represent the closeness between farmers and the service class and between farmers and the petty bourgeoisie in China. The adapted core model (model 4) fits the data much better than model 3, using two more affinity parameters but explaining a much larger

proportion of the origin-destination association ($G^2=211.5$ for men; 252.4 for women). It is also preferable to the model of constant social fluidity according to the BIC.

Models 5–10 are different variants of the hybrid model characterized by equation (1). First, the quasi-RC model (model 5) combines the linear-by-linear specification with six diagonal terms representing the class-specific tendencies of immobility. It also uses eight parameters to estimate the row scores and column scores directly from the data. The BIC suggests that the quasi-RC model (BIC=-664.3 for men; -620 for women) should be favored over the original core model (BIC=-515.5 for men; -310 for women) but not over the adapted core model (BIC=-669.7 for men; -627.2 for women). The quasi-RC model, however, may also be adapted by the incorporation of the Chinese-specific affinity effects. The resultant model (model 6) outperforms the adapted core model for women but not for men. Models 7–8 constitute the counterparts of models 5–6 in which equality constraints are imposed between the row scores and column scores such that $X_i^R = X_i^C$ for each i . In other words, they stipulate that the relative distances between the six classes are common to origin and destination. According to the BIC, the adapted quasi-RC model with equality constraints (model 8) is preferable to all previous models for both men and women (BIC=-689.7 for men; -634.2 for women). In models 9–10, the row scores and column scores were derived from external sources rather than estimated from the mobility data. Specifically, for each origin class and destination class, we constructed a measure of socioeconomic status (SES) using the sample median of the International Socioeconomic Index (ISEI, see Ganzeboom and Treiman 1996). The numbers are shown in Table III.3. We can see that for both men and women, farmers and farm laborers (IVc+VIIb) exhibit the lowest socioeconomic status, and the service class (I+II) stands much higher than the other groups. Using the SES as the row and column scores, the quasi-linear-by-linear model (model 9)

consumes fewer degrees of freedom than the quasi-RC model, but it fits the data much worse. However, when we augment the quasi-linear-by-linear model with the four Chinese affinity parameters (model 10), the model fits the data remarkably well, exhibiting the lowest BIC among all models for both men and women (BIC=-717.3 for men; -649.1 for women). We thus consider model 10 as the model that best characterizes a general pattern of class fluidity in China.

Besides the statistical criterion, we prefer model 10 to model 8 because the row scores and column scores can be more easily interpreted in the former. The fitted scores from model 8 are also reported in Table III.3. They do not accord well with the median ISEI in ranking the six classes. In particular, the estimated position of farming is much higher than the actual socioeconomic standing of farmers and farm laborers in China. For men, farming is placed even higher than skilled manual work. Such an unusual scoring of EGP classes, we believe, is primarily a result of the *hukou* system, which has presented the Chinese peasantry barriers to ordinary channels of upward mobility along the status hierarchy, and, in a peculiar way, pulled them closer than most blue collar workers to the class of the petty bourgeoisie and the service class.

The parameter estimates from model 10 are shown in the first and third columns of Table III.4, respectively for men and women. We draw several observations from the estimates. First, we find that the effect of status hierarchy is greater for women than for men, which echoes earlier research showing a stronger association between class origin and class destination for women than for men in China (Chen 2013; Cheng and Dai 1995). Second, consistent with patterns in many other countries, farmers and farm laborers exhibit the strongest tendency of immobility, followed by the class of the petty bourgeoisie. By contrast, the diagonal effect is negative and not statistically significant for the service class, suggesting that the managerial and

professional elite in China do not have an additional tendency towards immobility after the effects of status hierarchy are taken into account. Finally, all four affinity parameters are positive and highly significant, affirming the affinity between farmers and the service class and between farmers and the petty bourgeoisie in intergenerational mobility. It is noteworthy, moreover, that the effect of affinitive mobility from the farming class to the service class is greater for men than for women, whereas the reverse—affinitive mobility from the service class to the farming class—appears larger for women than for men. This is likely a result of the entrenched patriarchal mentality in rural China that has caused widespread gender disparities in parental investment and thus in occupational mobility (Hannum, Kong, and Zhang 2009; Hannum 2005).

Trends in Class Fluidity

On the basis of model 10, we now model trends in class fluidity across cohorts. The goodness-of-fit statistics for competing models are shown in the lower panel of Table III.2. First, we allow all parameters for origin-destination association—including effects of hierarchy, immobility, and affinity—to vary freely across cohorts, resulting in model 11. Although it fits the data much worse than model 10 according to the BIC, model 11 is useful in two respects. First, it serves as a benchmark against which more parsimonious models can be evaluated. Second, model 11 is equivalent to model 10 applied to the four cohorts separately. Thus we may detect important trends in class fluidity by comparing the parameter estimates across cohorts (shown in Table III.5). By doing so, we found that for both sexes, the effect of status hierarchy is considerably higher for the last cohort than for previous cohorts, which confirms our hypothesis that the link between origin and destination in socioeconomic status has tightened during the reform period. Second, we discovered significant variations from cohort to cohort in the effect of farm immobility. Specifically, immobility among farmers and farm laborers rose from the first cohort

to the second, and steadily declined thereafter. By contrast, neither the affinity effects nor the immobility effects for other classes exhibits noticeable trends beyond trendless fluctuations. Based on these observations, we now relax model 10 by allowing only the immobility effect for the farming class to be cohort-specific, and the effect of SES to differ between the first three cohorts and the last. The resultant model (model 12) fits the data extremely well, exhibiting a lower BIC than models 10 and 11 for both men and women. Moreover, for either sex, when compared with model 11, model 12 cannot be rejected at the 0.01 level according to the likelihood ratio test.

Finally, let us consider a Unidiff model (Erikson and Goldthorpe 1992; Xie 1992) where the structure of origin-destination association is the same as that specified in model 10. Under this model, the effects of hierarchy, immobility, and affinity are allowed to change in proportion to one another across cohorts (model 13). Compared with model 10, the Unidiff model fits the data fairly well, accounting for a sizeable portion of G^2 using only three degrees of freedom ($\Delta G^2=30.5$ for men, 27.9 for women). However, the BIC suggests that it is less favorable than model 12. The last row of Table III.2 reports the cohort-specific layer effects estimated under the Unidiff model, where a normalization constraint is applied such that the layer effect for the first cohort equals 1. We can see that for both men and women, the layer effect rises from cohort 1 to cohort 2 and falls thereafter, implying an inverted U-shaped trend in the overall origin-destination association. This trend, it should be noted, perfectly mirrors the inverted U-shaped trend in the effect of farming class immobility revealed by model 11, suggesting that the estimated layer effects of the Unidiff model may be predominantly driven by the trends in agricultural inheritance. In fact, when the farm-farm diagonal cells are blocked from the data, the Unidiff model does not yield significant variations by cohort (not shown). Hence, we prefer

model 12 to the Unidiff model not only because it is more probable according to Bayesian statistics but also because it enables us to disentangle two distinct trends in class fluidity that may be masked under a catch-all strength measure of origin-destination association.

We present the parameter estimates of model 12 in the second and fourth columns of Table III.4, for men and women respectively. On one hand, the interaction term between SES and cohort 4 indicates that the role of status hierarchy in class fluidity has significantly strengthened during the reform period: for both sexes, the estimated coefficient of SES is more than 50% larger for the late reform cohort (1972–1981) than for the previous three cohorts. To illustrate the tightening of the origin-destination link along the socioeconomic dimension, Figure III.3 plots the relationship between origin SES and the expected odds of entering the service class relative to the unskilled manual class under model 12 for the early reform cohort (1962–1971, shown in squares) and the late reform cohort (1972–1981, shown in circles). For both men and women, the circled line is consistently above the squared line, meaning that across the board, the odds of becoming a professional or manager relative to an unskilled manual worker increased from the third cohort to the last cohort. This overall shift reflects the rising proportion of service class jobs from the third to the last cohort as shown in Figure III.1. More importantly, for both sexes, the circled line exhibits a steeper slope than the squared line, suggesting an increase in the effect of origin SES on occupational attainment from the early reform period (around the 1980s) to the late reform period (since the 1990s). Therefore, we find strong support for our hypothesis that the link between origin and destination, especially along the socioeconomic dimension, has strengthened during China's transition from state socialism to a market economy. In addition, it should be noted that the boost in the odds at the very low end of origin SES in Figure III.3 results from the affinity effect between the farming and the service classes estimated under model 12.

On the other hand, model 12 allows the diagonal effect for the farming class to vary from cohort to cohort. Echoing results from the cohort-specific analyses (model 11), Table III.4 shows that class immobility among farmers and farm laborers declined sharply from the second cohort to the last cohort. That is, the sectoral barrier between farming and nonfarming occupations has become increasingly weaker over the past three decades. Given that industrialization and rural-urban migration have sped up in China during the same period, this finding accords with our hypothesis that exchange mobility between the agricultural and nonagricultural sectors tends to be higher in a rapidly industrializing society than under more stable economic conditions. It would be premature, however, to draw a causal inference based on temporal association in a single country. In the next subsection, we use cross-national data to examine more systematically the relationship between the pace of industrialization and the strength of the sectoral barrier to intergenerational mobility.

We also find a relatively low level of farm immobility for the first cohort (1936–1951). Detailed analyses of class-specific rates of outflow revealed that this is due to a particularly high rate of entry into agriculture from other classes in the first cohort (not shown). We think that this unusual flow of workers from nonfarming origin to farming destination is attributable to several historical episodes during the early years of the People’s Republic of China. First, the rural collectivization in the mid-1950s eliminated a vibrant commercial economy in the Chinese countryside, and, as a result, tens of millions of petty traders and self-employed craftsmen were transformed into land-bound peasants. Second, in the late 1950s, the campaign of the Great Leap Forward created an upsurge in rural industrial employment, especially in small-scale factories producing agricultural implements, fertilizers, and other consumer goods. However, since these factories were mostly inefficient and short-lived, many rural industrial workers were dismissed

and turned back to farming in the early 1960s. In addition, due to the establishment of the *hukou* system in 1958, a large volume of rural-urban migrant workers were forcibly sent back to their home villages in the late 1950s and early 1960s. A combination of these processes may have introduced substantial *intragenerational* mobility into agriculture from the 1950s to the early 1960s. Considering that the members of the first cohort were born between 1936 and 1951 and that their class origins are defined as their fathers' occupations when they were 14 years old, their relatively high rate of entry into agriculture is likely a result of the high intragenerational mobility into farming experienced by their fathers.

China in Comparative Perspective

The above analyses have shown that trends in class fluidity in China are characterized by (1) a strengthened status hierarchy, (2) a weakened barrier between the agricultural and nonagricultural sectors, and (3) relatively stable levels of affinity between farmers and the service class and between farmers and the petty bourgeoisie. We now put these trends in a broader context by comparing China with the 12 countries covered by the CASMIN project: Australia, England, France, West Germany, Hungary, Ireland, Japan, Northern Ireland, Poland, Scotland, Sweden, and the United States. It should be noted that mobility tables for these countries were all constructed from cross-sectional surveys in the 1970s. To compare the strengths of status hierarchy and class immobility in these countries with their trends in China, we fit a quasi-linear-by-linear model (model 9 in Table III.2) for each of the 12 countries and of the four Chinese cohorts. In this model, the median ISEI reported in Table III.3 are used as the row and column scores for all tables. The estimated effects of status hierarchy and farm immobility are shown in the first two columns of Table III.6. We note that while the effect of socioeconomic status in China has greatly strengthened in recent cohorts, it is still much weaker

than those in most CASMIN countries. In England, for instance, the estimated coefficient of hierarchy is about 20, about twice as large as that for Chinese men in the late reform cohort. The only country with a low socioeconomic effect comparable to China is Poland, where the Communist regime made a sustained effort to promote long-range social mobility in the post-war years (Erikson and Goldthorpe 1992: 160).¹² Thus, despite the sweeping market reforms and growing income inequality over the past 30 years, China today remains far more fluid along the socioeconomic dimension than most mature capitalist countries.

Further, farm immobility is lower for China's most recent cohort than in all the other countries, suggesting that the barrier between the agricultural and nonagricultural sectors is exceptionally weak in today's China. Moreover, the two countries that come closest to China are Hungary and Japan, both of which experienced rapid industrial expansion in the 1950s and 1960s, the period right before the CASMIN data were collected. At the other extreme, the highest effect of farming class immobility is found in England, a country that had long completed industrialization before the twentieth century. These observations accord well with our hypothesis that the boundary between agriculture and other sectors tends to be more permeable in rapidly industrializing countries than in advanced industrial societies. To visualize this relationship, we plot in Figure III.4 the degree of farm immobility against the pace of industrialization among the 12 CASMIN countries as well as the four Chinese cohorts. Here, the effects of farm immobility are exactly the numbers shown in the second column of Table III.6, and the pace of industrialization is measured by the difference between the proportion of farming

¹² Note that for all CASMIN countries, the data were collected in the 1970s. Class mobility in Poland may have changed significantly after the fall of communism in 1989.

class origins and the proportion of farming class destinations in each table.¹³ We can clearly see a negative relationship between the two: The quicker the pace of industrialization, the weaker the barrier between the agricultural and nonagricultural sectors. Hence, cross-national comparisons strongly suggest that the weakening of the sectoral barrier in China over the recent cohorts is a product of rapid industrialization and the concomitant rural-urban migration.

Finally, we compare China with the 12 CASMIN countries in terms of the affinity between farmers and the service class and between farmers and the petty bourgeoisie, with the logarithm of odds ratios for two 2×2 sub-tables extracted from the original data: the 2×2 tables containing farmers and the service class only and the 2×2 tables containing farmers and the petty bourgeoisie only. The log odds ratio gauges the relative degree of immobility versus affinity. In other words, the smaller the log odds ratio, the greater the relative strength of affinity. Because directly calculated log odds ratios often suffer from large sampling errors, we adopt their empirical Bayes estimates (Zhou 2015), which can effectively improve estimation precision and the accuracy of ranking among tables. The results are reported in the last two columns of Table III.6. For each 2×2 table, China exhibits the lowest log odds ratio among all countries except the United States, in which the log odds ratio between farmers and the petty bourgeoisie is lower than in China. The two patterns of affinity, therefore, are in large measure distinctively Chinese phenomena. As discussed earlier, they are unique products of the Chinese household registration system, which has unintentionally yet significantly distorted the channel of intergenerational mobility into and out of peasantry.

¹³ This difference is not an optimal measure of generational change in the share of agricultural employment because it does not take into account differential fertility and mortality between farming and nonfarming populations. It nonetheless is a reasonable proxy for the pace of industrialization and should serve our purpose of cross-national comparisons well.

Sensitivity Analysis

In our examination of trends in class mobility, we divided the sample into four birth cohorts and interpreted cohort differences as resulting from forces of market transition and rapid industrialization over the past three decades in China. The observed trends by cohort, however, could also be driven by age or period effects. On the one hand, since our survey data span only 16 years (1996–2012), cohort and age are strongly correlated in our cumulative sample. That is, later cohorts are likely younger than earlier cohorts. Although our analysis included only workers who were at least 31 years old, further life cycle effects might still have exerted an influence. On the other hand, cohort is associated with survey period because more recent surveys are more likely to cover later cohorts than earlier cohorts. Thus the observed differences by cohort could also be contaminated by short-term period trends from 1996 to 2012.

Recognizing the intractability of separating out the effects of age, period, and cohort simultaneously, we carried out two sensitivity checks by controlling for age and period separately. First, given that three of the six surveys—LHSCCC 1996, CGSS 2006, and CGSS 2008—also collected information on the respondent’s first job, we restricted our sample to these three data sets, recoded class destination as the respondent’s first job, and reran model 12 for the corresponding data. Since different workers take up their first jobs within a relatively short age range, potential life cycle effects that may contaminate cohort differences are minimized if not eliminated. The results are reported in the first two columns of Table III.7. All patterns and trends using data on the first job are consistent with our main results on the current job shown earlier in Table III.4, except that the effect of farming class immobility seems not to decline until the last cohort. Considering that the third cohort (1962–1971) mostly entered the labor market in the 1980s, we may infer that the weakening of the sectoral barrier did not start until the 1990s.

Second, to control for period effects, we applied model 12 to data from CGSS 2010 and CGSS 2012 only. Since only a few respondents in the first cohort (1936–1951) were covered in the 2010 and 2012 surveys, we restricted the analysis to the later three cohorts. The results are shown in the last two columns of Table III.7. We can see that most coefficients are statistically significant and in the expected direction. One exception is that the effect of affinity for movement from farm to the service class is very small and not significantly different from zero, suggesting that this uniquely Chinese channel of long-range upward mobility may have been closed off during the most recent years. Overall, the results from these two sensitivity analyses are highly consistent with our main findings. We therefore stand by our cohort-based explanations for trends in social fluidity.

Conclusion

In this study, we adopt a cohort perspective to examine trends in social mobility in the People's Republic of China. Absolute rates of mobility, especially of upward mobility, have grown substantially from the cohort born in the 1950s to that born in the 1970s. This growth, however, has been entirely driven by the force of industrialization—that is, the placement of an increasingly larger share of children of farming origin into nonfarming occupations. Trends in social fluidity, however, are much less clear-cut, confounded by two contradicting forces. On the one hand, the influence of status hierarchy on class transmission has significantly heightened during China's transition to a market economy, as reflected by a large increase (more than 50%) in the origin-destination association in socioeconomic status from the early reform cohort to the late reform cohort. On the other hand, the degree of immobility among farmers and farm laborers has declined sharply over the recent cohorts, suggesting that the boundary between the agricultural and nonagricultural sectors has become more permeable during China's rapid

industrialization since the 1980s and especially in the 1990s. Characterized by a strengthened status hierarchy and a weakened sectoral barrier, the recent trends in class fluidity in China defy a unidirectional portrayal.

To shed more light on the institutional and economic determinants of social fluidity, we have placed the trends in China in an international context by comparing the four Chinese cohorts with cross-sections of the 12 advanced industrial countries covered in the CASMIN project. Three findings have emerged. First, the link between origin and destination in socioeconomic standing was exceptionally weak under Chinese state socialism. As a result, despite a consolidation of the status hierarchy during the reform period, the influence of origin SES on class attainment is still far weaker in today's China than in mature capitalist countries. Second, cross-national comparisons reveal a strong negative relationship between the pace of industrialization and the strength of the sectoral barrier between farming and nonfarming occupations. Thus, the weakening of the sectoral barrier in China is in all likelihood a result of rapid industrialization and the massive rural-urban migration that has been occurring since the 1980s. Finally, the two patterns of affinity—disproportionate flows between farmers and the service class and between farmers and the petty bourgeoisie—are in large measure distinctively Chinese phenomena, consonant with our *hukou*-based accounts of patterns of mobility into and out of peasantry.

This study contributes to two strands of literature in social stratification. First, it provides new insights into the ways in which institutional transition shapes intergenerational mobility. While Gerber and Hout (2004) have demonstrated a decline in the overall degree of class fluidity following the collapse of communism in Russia, the present study emphasizes that the impact of market transition on social mobility is primarily through a fortification of the status hierarchy. In

China as well as other post-socialist countries, the emergence of markets provided abundant opportunities for the old elites to convert their political power into physical capital, thus making socioeconomic status far more inheritable than before. Meanwhile, a more market-driven reward system spurred a sharp increase in income inequality, thereby equipping upper-class families with more resources and incentives to pass their economic advantages on to their offspring. The abolition of egalitarian educational policies, moreover, severely limited the channel of upward mobility for children of socioeconomically disadvantaged families. A combination of these processes may well explain the consolidation of status hierarchy and its influence on social fluidity.

However, we have also shown that China's experience has markedly differed from that of Russia due to a counterbalancing effect of rapid industrialization. In understanding the dual forces of market transition and industrialization in China, our study offers a new perspective for assessing the influence of industrialization on social stratification. In contrast to the thesis of industrialism and the FJH hypothesis, this perspective highlights the pace of industrialization—rather than the level of industrialization—as a crucial force shaping social fluidity, especially the degree of relative mobility between the agricultural and nonagricultural classes. Cross-national evidence strongly supports our conjecture that the sectoral barrier tends to be weaker during periods of rapid industrialization than under more stable economic conditions. Indeed, a common feature shared by most, if not all, rapidly industrializing societies is the prevalence of part-time farmers who take advantage of opportunities for industrial employment yet retain their ties to the land. By straddling the agricultural and industrial sectors, these part-time farmers effectively weaken the role of the sectoral boundary in intergenerational class transmission. This unique linkage between rapid industrialization and inter-sectoral mobility has profound implications for

comparative stratification research, as the literature has only recently begun to go beyond the developed world to study newly industrialized countries in Asia and Latin America (Ishida 2008; Torche 2014).

The above two contributions further illustrate that social mobility is a process of multiple dimensions and should be analyzed as such. Status hierarchy shapes the class destinations of those who move out of their class origins, class immobility reflects a degree of social closure that affects the likelihood of mobility per se, and the sectoral barrier gauges the extent to which macroeconomic structure constrains the specific flows of manpower. Although the multidimensionality of occupational mobility has long been recognized among stratification scholars (e.g., Erikson and Goldthorpe 1987; Hout 1984; Wong 1992), it has received scant attention in theoretical formulations that aim to explain temporal trends or spatial variations. Indeed, almost all existing macro-sociological explanations for variations in social fluidity across time and space—including hypotheses regarding industrialization, educational expansion, political ideology, economic inequality, and cultural exceptionalism—implicitly treated social fluidity as a unidimensional construct, and, as a result, so did most empirical assessments of these hypotheses. If, as this study suggests, different dimensions of the mobility process are driven by different societal forces, researchers would want to study dimension-specific patterns of spatial-temporal variation in social mobility. A unidimensional approach would be theoretically incomplete and analytically inadequate. We believe that future research on comparative mobility will benefit from a fuller appreciation of a multi-dimensional approach.

Figure III.1 Trends in Distribution of Class Destinations across the Four Cohorts.

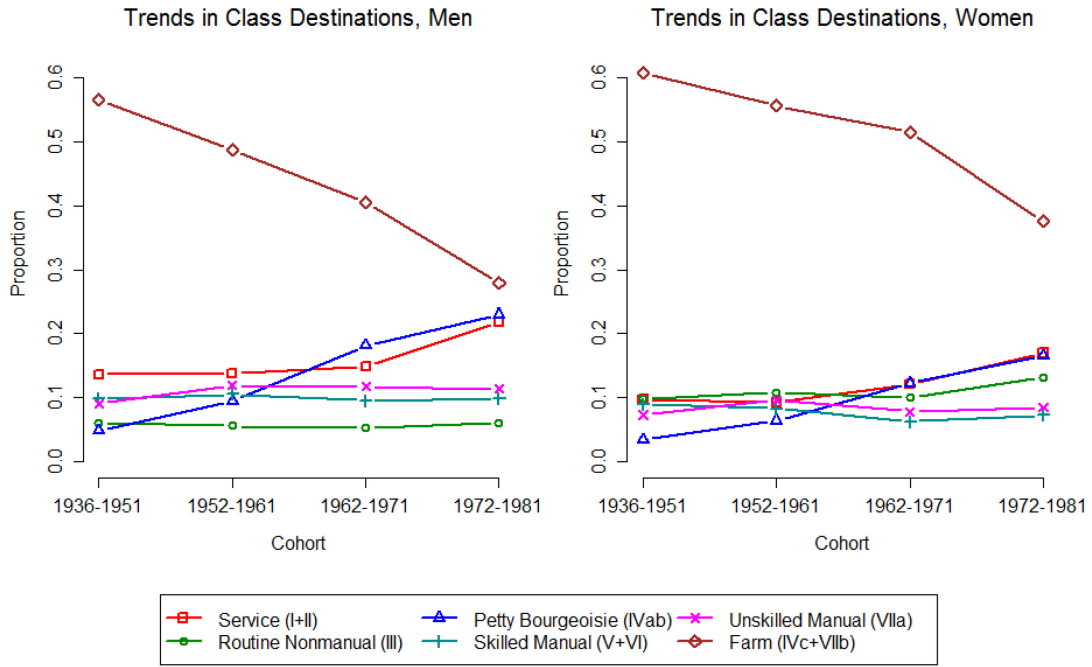


Figure III.2 Trends in Absolute Mobility Rates across the Four Cohorts.

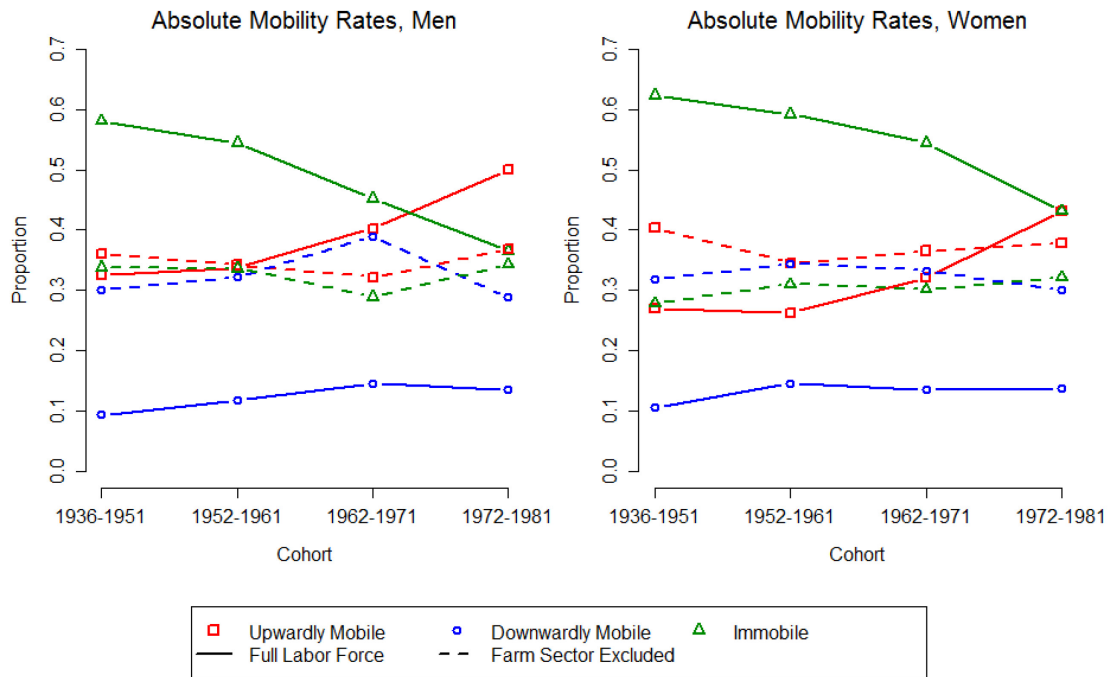


Figure III.3 Expected Odds on Service (I+II) relative to Unskilled Manual Work (VIIa) under model 12.



Figure III.4 Degree of Farm Immobility versus Pace of Industrialization among 16 Mobility Tables.



Table III.1 The EGP Class Scheme: Origin Version and the Six-Category Version

Original Version	Six-category Version
I. Large proprietors, higher professionals and managers,	I+II. The service class
II. Lower professionals and managers	
III. Routine non-manual workers	III. Routine non-manual workers
IVa. Small proprietors with employees	IVab. The petty bourgeoisie
IVb. Small proprietors without employees	
V. Lower grade technicians and manual supervisors	V+VI. Skilled manual workers
VI. Skilled manual workers	
VIIa. Unskilled and semiskilled manual workers	VIIa. Unskilled manual workers
IVc. Self-employed farmers	IVc+VIIb. Farmers
VIIb. Agricultural laborers	

Table III.2 Goodness-of-Fit Statistics for Competing Models of Social Fluidity

	<i>df</i>	G^2	Men <i>p</i>	BIC	G^2	Women <i>p</i>	BIC
<i>Models for Patterns of Fluidity</i>							
1. Conditional Independence	100	3901.7	0.00	2933.4	4930.5	0.00	3964.0
2. Constant Social Fluidity	75	110.8	0.00	-615.5	144.3	0.00	-580.6
3. Core Model	93	385.0	0.00	-515.5	588.8	0.00	-310.0
4. Core Model with Chinese Affinity Parameters	91	211.5	0.00	-669.7	252.4	0.00	-627.2
5. Quasi-RC (II)	85	158.8	0.00	-664.3	201.5	0.00	-620.0
6. Quasi-RC (II) +Chinese Affinity Parameters	81	128.8	0.00	-655.6	149.7	0.00	-633.2
7. Quasi-RC (II) with Equality Constraints	89	196.2	0.00	-665.6	308.8	0.00	-551.4
8. Quasi-RC (II) with Equality Constraints + Chinese Affinity Parameters	85	133.4	0.00	-689.7	187.3	0.00	-634.2
9. Quasi-Linear-by-Linear	93	408.0	0.00	-492.6	587.4	0.00	-311.5
10. Quasi-Linear-by-Linear +Chinese Affinity Parameters (Preferred model)	89	144.5	0.00	-717.3	211.2	0.00	-649.1
<i>Models for Trends across Cohorts</i>							
11. Model 10 with All Parameters Varying with Cohort	56	67.4	0.14	-474.9	114.5	0.00	-426.8
12. Model 10 + Cohort-varying Farm Immobility + SES*Cohort 4 (Preferred model)	85	98.2	0.16	-724.9	165.0	0.00	-656.6
Model 12 vs. Model 11	31	31.2	0.46		50.5	0.015	
13. Model 10 with Unidiff Association by Cohort	86	114.0	0.02	-718.8	183.3	0.00	-647.9
Layer Effects				$\phi_1 = 1; \phi_2 = 1.33;$ $\phi_3 = 1.17; \phi_4 = 1.08;$	$\phi_1 = 1; \phi_2 = 1.10;$ $\phi_1 = 0.96; \phi_2 = 0.85;$		

Note: The core model is adjusted to the six-class EGP scheme. The linear-by-linear association model uses the median ISEI within each origin and destination class as the corresponding row or column score. The Chinese affinity parameters are used to capture disproportionate flows between farmers (IVc+VIIb) and the service class (I+II) and between farmers (IVc+VIIb) and the petty bourgeoisie (IVab).

Table III.3 Median ISEI and Fitted Scores from Model 8 for Origin and Destination Classes

	I+II	III	IVab	V+VI	VIIa	IVc+VIIIb
<i>Men</i>						
ISEI, Origin	66	45	33	34	29	23
ISEI, Destination	65	43	34	34	30	23
Fitted Score	0.56	0.33	0.06	-0.10	-0.52	0.01
<i>Women</i>						
ISEI, Origin	66	45	34	34	29	23
ISEI, Destination	59	43	37	34	29	23
Fitted Score	0.40	0.47	0.47	-0.13	-0.48	-0.32

Table III.4 Parameters Estimates and Fit Statistics for Model 10 and Model 12

	Men		Women	
	Model 10	Model 12	Model 10	Model 12
<i>Hierarchy</i>				
SES/100	8.36*** (1.49)	7.71*** (1.50)	11.45*** (1.47)	10.47*** (1.49)
SES/100 * Cohort 4		4.17*** (1.13)		6.44*** (1.43)
<i>Immobility</i>				
Service (I+II)	-0.21 (0.15)	-0.23 (0.15)	-0.07 (0.12)	-0.10 (0.12)
Routine Non-manual (III)	0.25* (0.11)	0.25* (0.11)	0.28*** (0.08)	0.29*** (0.08)
Petty Bourgeoisie (IVab)	1.28*** (0.12)	1.28*** (0.12)	0.91*** (0.15)	0.92*** (0.15)
Skilled Manual (V+VI)	0.67*** (0.07)	0.67*** (0.07)	0.38*** (0.08)	0.38*** (0.08)
Unskilled Manual (VIIa)	0.23** (0.08)	0.23** (0.08)	0.13 (0.09)	0.13 (0.09)
Farm (IVc+VIIb)	2.56*** (0.07)		2.72*** (0.07)	
Farm, Cohort 1		2.21*** (0.12)		2.82*** (0.13)
Farm, Cohort 2		2.93*** (0.11)		3.03*** (0.10)
Farm, Cohort 3		2.63*** (0.10)		2.68*** (0.09)
Farm, Cohort 4		2.06*** (0.15)		2.01*** (0.14)
<i>Affinity</i>				
Service to Farm	0.97*** (0.11)	0.96*** (0.12)	1.27*** (0.11)	1.25*** (0.11)
Farm to Service	0.44*** (0.09)	0.44*** (0.09)	0.22** (0.08)	0.22** (0.08)
Petty Bourgeoisie to Farm	0.77*** (0.17)	0.71*** (0.17)	0.99*** (0.15)	0.90*** (0.15)
Farm to Petty Bourgeoisie	0.82*** (0.06)	0.81*** (0.06)	0.94*** (0.07)	0.91*** (0.07)
G^2	144.5	98.2	211.2	165.0
Df	89	85	89	85

Note: †p<.1, *p<.05, **p<.01, ***p<.001 (two-tailed tests). Numbers in parentheses are standard errors.

Table III.5 Cohort-Specific Results for the Quasi-Linear-by-Linear Model with Chinese Affinity Parameters

	Men					Women				
	All Birth Cohorts	1936-1951	1952-1961	1962-1971	1972-1981	All Birth Cohorts	1936-1951	1952-1961	1962-1971	1972-1981
<i>Hierarchy</i>										
SES	8.36*** (1.49)	7.02† (3.70)	6.61* (2.80)	8.11*** (2.45)	13.48*** (3.45)	11.45*** (1.47)	5.81 (4.20)	11.32*** (2.73)	11.08*** (2.39)	17.20*** (3.33)
<i>Immobility</i>										
Service (I+II)	-0.21 (0.15)	-0.16 (0.39)	0.08 (0.29)	-0.41 (0.25)	-0.39 (0.35)	-0.07 (0.12)	0.29 (0.36)	-0.25 (0.23)	0.01 (0.19)	-0.31 (0.25)
Routine Non-manual (III)	0.25* (0.11)	0.46† (0.26)	0.26 (0.20)	0.30 (0.19)	-0.14 (0.32)	0.28*** (0.08)	0.32 (0.22)	0.52*** (0.15)	0.10 (0.14)	0.26 (0.19)
Petty Bourgeoisie (IVab)	1.28*** (0.12)	1.88*** (0.39)	1.43*** (0.26)	1.07*** (0.21)	1.24*** (0.22)	0.91*** (0.15)	0.20 (0.76)	1.07** (0.35)	1.05*** (0.25)	0.80*** (0.23)
Skilled Manual (V+VI)	0.67*** (0.07)	0.55** (0.18)	0.73*** (0.13)	0.61*** (0.12)	0.82*** (0.19)	0.38*** (0.08)	0.02 (0.21)	0.38** (0.14)	0.57*** (0.13)	0.22 (0.22)
Unskilled Manual (VIIa)	0.23** (0.08)	0.35† (0.21)	0.31* (0.14)	0.23 (0.14)	-0.10 (0.22)	0.13 (0.09)	-0.12 (0.28)	0.23 (0.15)	0.13 (0.15)	-0.04 (0.26)
Farm (IVc+VIIb)	2.56*** (0.07)	2.07*** (0.16)	3.12*** (0.14)	2.59*** (0.13)	2.05*** (0.20)	2.72*** (0.07)	3.11*** (0.19)	3.18*** (0.13)	2.64*** (0.11)	1.70*** (0.16)
<i>Affinity</i>										
Service to Farm	0.97*** (0.11)	0.76** (0.27)	1.36*** (0.22)	0.75*** (0.19)	1.02*** (0.30)	1.27*** (0.11)	1.57*** (0.31)	1.48*** (0.21)	1.18*** (0.18)	0.77** (0.28)
Farm to Service	0.44*** (0.09)	0.33 (0.21)	0.45** (0.16)	0.47** (0.15)	0.46* (0.20)	0.22** (0.08)	0.08 (0.22)	0.25 (0.16)	0.33* (0.13)	0.07 (0.18)
Petty Bourgeoisie to Farm	0.77*** (0.17)	0.12 (0.42)	1.12*** (0.33)	0.60† (0.31)	0.91** (0.34)	0.99*** (0.15)	0.50 (0.41)	1.38*** (0.28)	1.12*** (0.26)	0.39 (0.29)
Farm to Petty Bourgeoisie	0.82*** (0.06)	0.79*** (0.22)	0.78*** (0.12)	0.92*** (0.09)	0.68*** (0.13)	0.94*** (0.07)	1.22*** (0.28)	1.21*** (0.14)	0.89*** (0.10)	0.65*** (0.13)
G^2	144.5	20.1	11.6	26.2	9.5	211.2	10.6	39.8	27.4	36.7
df	89	14	14	14	14	89	14	14	14	14

Note: †p<.1, *p<.05, **p<.01, ***p<.001 (two-tailed tests). Numbers in parentheses are standard errors.

Table III.6 Cross-national Comparisons in Hierarchy, Farm Immobility, and Affinities

	Quasi-linear-by-linear Model (without Affinity Parameters)		Log Odds Ratios for 2×2 Subtables (Empirical Bayes Estimates)	
	Hierarchy	Farm Immobility	(Service, Farm)	(Petty Bourgeoisie, Farm)
China: Cohort 1	2.61	1.81		
China: Cohort 2	0.62	2.52		
China: Cohort 3	5.51	1.97	2.52	2.57
China: Cohort 4	10.35	1.40		
Australia	21.36	1.94	3.61	2.90
England	20.47	2.99	4.65	3.75
France	21.95	2.70	5.59	3.97
West Germany	23.04	2.58	4.80	4.49
Hungary	24.47	1.66	4.39	3.48
Ireland	17.04	2.79	4.72	3.90
Japan	15.43	1.75	3.17	3.33
Northern Ireland	16.91	3.04	4.66	3.54
Poland	10.13	2.38	4.89	3.47
Scotland	19.49	3.21	4.63	3.67
Sweden	23.94	1.85	4.38	3.01
USA	19.18	1.99	3.87	2.38

Note: Results in this table are for men only. The quasi-linear-by-linear model uses the median ISEI presented in Table III.3 as the row and column scores for all tables.

Table III.7 Parameters Estimates and Fit Statistics for model 12 under Alternative Specifications

	First Job		2010+2012 Data Only	
	Men	Women	Men	Women
<i>Hierarchy</i>				
SES	12.21*** (2.73)	11.62*** (2.38)	8.94** (2.92)	16.50*** (2.36)
SES*Cohort 4	2.69† (1.63)	4.70** (1.69)	5.55* (2.17)	5.41* (2.59)
<i>Immobility</i>				
Service (I+II)	-0.65* (0.31)	-0.33 (0.24)	-0.18 (0.21)	-0.13 (0.15)
Routine Non-manual (III)	0.81*** (0.19)	0.96*** (0.14)	0.23 (0.19)	0.10 (0.13)
Petty Bourgeoisie (IVab)	1.73*** (0.25)	1.68*** (0.27)	1.27*** (0.16)	0.78*** (0.19)
Skilled Manual (V+VI)	0.58*** (0.11)	0.12 (0.12)	0.61*** (0.13)	0.10 (0.15)
Unskilled Manual (VIIa)	0.25* (0.12)	0.01 (0.13)	0.32* (0.13)	0.09 (0.16)
Farm, Cohort 1	2.11*** (0.15)	2.86*** (0.17)		
Farm, Cohort 2	2.30*** (0.14)	2.83*** (0.14)	2.78*** (0.17)	3.00*** (0.16)
Farm, Cohort 3	2.59*** (0.13)	2.83*** (0.13)	2.36*** (0.16)	2.27*** (0.14)
Farm, Cohort 4	2.27*** (0.19)	2.26*** (0.18)	1.89*** (0.20)	2.16*** (0.19)
<i>Affinity</i>				
Service to Farm	0.67*** (0.17)	1.03*** (0.16)	0.68*** (0.18)	1.20*** (0.16)
Farm to Service	1.21*** (0.16)	0.65*** (0.15)	0.03 (0.13)	0.01 (0.13)
Petty Bourgeoisie to Farm	0.45* (0.23)	0.36 (0.25)	0.92*** (0.25)	1.18*** (0.20)
Farm to Petty Bourgeoisie	0.83*** (0.16)	1.07*** (0.15)	0.71*** (0.09)	0.93*** (0.10)
G^2	137.4	162.1	53.1	127.5
<i>Df</i>	85	85	61	61

Note: †p<.1, *p<.05, **p<.01, ***p<.001 (two-tailed tests). Numbers in parentheses are standard errors. Data source: LHSCCC 1996, CGSS 2006, CGSS 2008 for left panel; CGSS 2010, CGSS 2012 for right panel.

CHAPTER IV Shrinkage Estimation of Log Odds Ratios for Comparing Mobility Tables

Comparative mobility analysis has long been at the core of social stratification research. To investigate how patterns of intergenerational mobility differ across countries or vary over time, stratification researchers typically compare a collection of mobility tables that cross-classify fathers and sons by their occupations or classes. To draw such comparisons, researchers until the 1970s had relied on simple calculations of inflow and outflow rates (e.g., Lipset and Zetterberg 1956; Miller 1960) or the construct of “mobility ratios” (e.g., Glass and Berent 1954; Rogoff 1953), both of which turned out to be inadequate to separate changes in relative mobility (also known as exchange mobility, circulation mobility, or social fluidity) from changes in marginal distributions (i.e., structural mobility).¹⁴ Beginning in the late 1960s, thanks to the pioneering work of Leo Goodman (1968, 1969), it has been recognized that all associations in an $I \times J$ contingency table can be captured by a sufficient set of $(I - 1)(J - 1)$ odds ratios.¹⁵ This fundamental discovery paved the way for the subsequent development of log-linear and log-multiplicative models (e.g., Duncan 1979; Goodman 1979; Hauser 1980), in which the natural logarithms of odds ratios are expressed as regression coefficients or their linear combinations.

Given the centrality of odds ratios in depicting the structure of row-column association, a natural approach to comparing mobility tables, as suggested by Goodman (1969), is to directly

¹⁴ The inadequacy of mobility ratio as a measure of association has been discussed by Blau and Duncan (1967, p.93-97), Tyree (1973), Hauser (1980, p.426-430), and Hout (1983, p.17-18).

¹⁵ Typically, the same occupational classification is used for origin and destination, i.e., fathers and sons. In this case, $I = J$.

compare their corresponding (log) odds ratios in search of similarities and differences. Although mobility studies in sociology have been dominated by log-linear modeling since the 1970s, this older model-free approach has its own appeal because it allows a panoramic view of the association between origin and destination without invoking parametric assumptions (see Hout and Guest [2013] for an illustration). Meanwhile, using log odds ratios as building blocks, Altham (1970) proposed a number of aggregate measures of association for comparing contingency tables. One of these measures (see the section Adjusted Estimation of the Altham Index) has been recently employed to examine long-term trends in occupational mobility in Great Britain and the United States (Ferrie 2005; Long and Ferrie 2007, 2013).

Unlike log-linear modeling, the model-free approach to comparing mobility tables imposes no parametric constraints on the pattern of association between origin and destination. Instead, it requires that every log odds ratio be estimated separately from data. Estimation of single log odds ratios, however, can be highly imprecise in practice. Indeed, the usual maximum likelihood estimator (MLE) of the log odds ratio— that is, $\log \frac{n_{11}n_{22}}{n_{12}n_{21}}$ —will be accompanied by a large standard error unless all of the associated cells contain many cases,¹⁶ a condition that often fails for real mobility tables. As a result, direct comparisons in sample log odds ratios across tables are prone to conflate true variations in relative mobility with sampling fluctuations. On the one hand, if relative mobility is constant and trendless in all complex societies, as implied by the hypothesis of constant social fluidity (Erikson and Goldthorpe 1992; Featherman, Jones, and Hauser 1975; Grusky and Hauser 1984), the observed differences will stem entirely from

¹⁶ This observation derives from the fact that an estimated variance of the sample log odds ratio can be expressed as $1/n_{11} + 1/n_{12} + 1/n_{21} + 1/n_{22}$ (Agresti 2002, p.71). See also the next section.

sampling and measurement errors. On the other hand, if social fluidity does differ across countries and change over time, sampling variability may also contaminate empirical comparisons between mobility regimes. In particular, when the set of mobility tables under investigation vary greatly in sample size, the relatively sparse tables are more likely to be estimated at the extremes of the mobility spectrum because they are subject to larger sampling errors. Because sample size is presumably unrelated to the true amount of social fluidity, this statistical artifact may distort the rank order of mobility regimes in the size of origin-destination association. Such a distortion can be substantively significant unless sampling errors are negligible relative to systematic variations among mobility regimes. The latter condition, unfortunately, seldom holds in comparative mobility research.

In log-linear modeling, estimation uncertainty is partly alleviated through parametric assumptions. For example, the constant social fluidity (CSF) model assumes no cross-table variation in all log odds ratios, and the Unidiff model (Xie 1992; Erikson and Goldthorpe 1992) stipulates that the relative magnitudes of different log odds ratios are uniform in all tables. These assumptions, however, may accord poorly with real data. In this paper, I propose a shrinkage method for estimating log odds ratios that attempts to enhance estimation efficiency without explicitly constraining the patterns of row-column association. Building on an empirical Bayes model (Efron and Morris 1973; Fay and Herriot 1979), the shrinkage estimator “borrows strength” across multiple tables while placing no restrictions on the structure of association within tables. As I will show by simulation, the shrinkage method leads to lower total squared errors than does the usual MLE of the log odds ratio. More important, when tables vary greatly in sample size—a situation that we often encounter in comparative mobility analysis—the shrinkage estimates exhibit markedly higher correlations with the true log odds ratios than do the usual estimates.

Therefore, the shrinkage method can enhance the accuracy of cross-table comparisons in the degree of row-column association. Moreover, the shrinkage estimates of log odds ratios can be used to calculate summary measures of association that are based on aggregations of log odds ratios. To illustrate this point, I construct an adjusted estimator of the Altham index (Altham 1970; Altham and Ferrie 2007), and, with a set of calibrated simulations, demonstrate its usefulness in enhancing both the precision of individual estimates and the accuracy of cross-table comparisons. Finally, using two sets of real mobility tables, I show that in gauging the overall degree of social fluidity, the adjusted estimates of the Altham index agree more closely with results from the Unidiff model than do direct estimates of the Altham index.

Shrinkage Estimation of Log Odds Ratios

Usual Estimator of the Log Odds Ratio

Let us consider K 2×2 contingency tables, which, say, cross-classify fathers and sons according to nonmanual and manual classes in K countries. Denoting by n_{ijk} the cell frequency pertaining to the i th row and the j th column in country k , the observed log odds ratios for these tables can be expressed as

$$Y_k = \log \frac{n_{11k}n_{22k}}{n_{12k}n_{21k}}, \quad k = 1, 2, \dots, K. \quad (1)$$

Assuming a multinomial sampling distribution for each country, these sample log odds ratios are also the maximum likelihood estimates (MLE) of population log odds ratios.¹⁷ They are therefore asymptotically normal—that is,

$$\sqrt{n_{++k}}(Y_k - \theta_k) \xrightarrow{d} N(0, V_k),$$

¹⁷ The same conclusion holds when the sampling distribution is Poisson or product-multinomial. See Powers and Xie (2008, p.79-80).

where n_{++k} and θ_k represent the sample size and the population log odds ratio for country k .

Using the delta method, it is not hard to show that the asymptotic variance of Y_k is

$$\sigma_k^2 = \frac{V_k}{n_{++k}} = \frac{1}{n_{++k}\pi_{11k}} + \frac{1}{n_{++k}\pi_{12k}} + \frac{1}{n_{++k}\pi_{21k}} + \frac{1}{n_{++k}\pi_{22k}},$$

where the π_{ijk} 's denote the unknown cell probabilities (Agresti 2002:75–76).

Substituting the observed proportions for the π_{ijk} 's, we obtain a sample estimate of σ_k^2 :

$$\widehat{\sigma}_k^2 = \frac{1}{n_{11k}} + \frac{1}{n_{12k}} + \frac{1}{n_{21k}} + \frac{1}{n_{22k}}. \quad (2)$$

Because there is a finite, however small, probability that any of the four cells are zero, the observed log odds ratio (1) may equal ∞ or $-\infty$. In such cases, a common practice is to add one-half to all of the four cell frequencies, yielding a modified estimator (Agresti 2002:71)

$$\widetilde{Y}_k = \log \frac{(n_{11k}+0.5)(n_{22k}+0.5)}{(n_{12k}+0.5)(n_{21k}+0.5)}.$$

Haldane (1956) shows that this modification reduces the sampling bias from the order of $O(n^{-1})$ to the order of $O(n^{-2})$. Moreover, Gart and Zweifel (1967) note that the corresponding variance estimator

$$\widetilde{\sigma}_k^2 = \frac{1}{n_{11k}+0.5} + \frac{1}{n_{12k}+0.5} + \frac{1}{n_{21k}+0.5} + \frac{1}{n_{22k}+0.5}$$

is an unbiased estimator of $\text{Var}(\widetilde{Y}_k)$ except for terms of $O(n^{-3})$. I therefore adopt these adjustments in the case of zero cells throughout the rest of the paper.¹⁸

Since the observed log odds ratio (1) coincides with the MLE, it is consistent and asymptotically efficient. Nonetheless, the asymptotic variance estimator (2) indicates that the

¹⁸ Clogg and Eliason (1987) noted that the practice of adding constants to all cells tends to shrink the data toward equiprobability. As we will see, this problem will be less relevant for the shrinkage estimator because the modified sample estimate Y_k is unlikely to receive much weight when there are zero cells.

MLE can be highly imprecise in small samples: Unless all of the four cells contain many cases, the standard error will be very large. As a result, if we directly compare the observed log odds ratios from different tables, those from relatively sparse tables will be more likely to be ranked at the extremes. This is undesirable because sample size is presumably unrelated to the true degree of association. The shrinkage approach I present below aims to improve both the precision of estimates from sparse tables and the accuracy of ranking among different mobility regimes.

Empirical Bayes Shrinkage

To explicate the shrinkage approach, let us first accept the normal approximations of the observed log odds ratios—that is,

$$Y_k | \theta_k \stackrel{\text{indep}}{\sim} N(\theta_k, \widehat{\sigma}_k^2). \quad (3)$$

Now consider a Bayes model where the population log odds ratios themselves follow a normal prior

$$\theta_k \stackrel{\text{i.i.d.}}{\sim} N(\mu, \tau^2), \quad (4)$$

where μ and τ^2 are hyperparameters representing the prior mean and the prior variance of the unknown θ_k 's. It is easy to show that the posterior distribution of θ_k is also normal, and the Bayes estimator, i.e., the posterior mean, can be written as

$$E(\theta_k | Y_k) = \mu + \left(1 - \frac{\widehat{\sigma}_k^2}{\tau^2 + \widehat{\sigma}_k^2}\right)(Y_k - \mu). \quad (5)$$

Estimating the hyperparameters μ and τ^2 directly from the data, say, through maximizing the marginal likelihood, leads to an empirical Bayes estimator (Efron and Morris 1973, 1975)

$$\widehat{\theta}_k^{\text{EB}} = \widehat{\mu} + \left(1 - \frac{\widehat{\sigma}_k^2}{\widehat{\tau}^2 + \widehat{\sigma}_k^2}\right)(Y_k - \widehat{\mu}). \quad (6)$$

In the statistics literature, $\hat{\theta}_k^{\text{EB}}$ has been described as a shrinkage estimator because it “shrinks” the observed outcome Y_k toward the estimated prior mean $\hat{\mu}$ with a shrinkage factor of $\frac{\widehat{\sigma}_k^2}{\tau^2 + \widehat{\sigma}_k^2}$.

The shrinkage factor, clearly, depends on the precision of the observation Y_k : the larger is the sampling variance $\widehat{\sigma}_k^2$, the stronger is the degree of shrinkage. Indeed, the empirical Bayes estimator can be expressed as a precision-weighted average between Y_k and $\hat{\mu}$ (Raudenbush and Bryk 1985, 2002):

$$\hat{\theta}_k^{\text{EB}} = \frac{1/\widehat{\tau}^2}{1/\widehat{\tau}^2 + 1/\widehat{\sigma}_k^2} \hat{\mu} + \frac{1/\widehat{\sigma}_k^2}{1/\widehat{\tau}^2 + 1/\widehat{\sigma}_k^2} Y_k ,$$

where the weight accorded to Y_k is proportional to its sampling precision $1/\widehat{\sigma}_k^2$ and the weight accorded to $\hat{\mu}$ is proportional to $1/\widehat{\tau}^2$, a measure of the concentration of the unknown θ_k 's around the prior mean μ .

Since the shrinkage factor in the posterior mean (5) is a convex function of the prior variance τ^2 , a substitution of a nearly unbiased estimate $\widehat{\tau}^2$ for τ^2 would produce an upward bias for the shrinkage factor $\frac{\widehat{\sigma}_k^2}{\tau^2 + \widehat{\sigma}_k^2}$ (by Jensen's inequality). To alleviate this problem, Morris (1983) suggested that the estimator (6) be replaced by

$$\hat{\theta}_k^{\text{EB}} = \hat{\mu} + \left[1 - \frac{(K-3)\widehat{\sigma}_k^2}{(K-1)(\widehat{\tau}^2 + \widehat{\sigma}_k^2)} \right] (Y_k - \hat{\mu}) , \quad (7)$$

where the multiplying constant $\frac{K-3}{K-1}$ is used to offset the bias of $\frac{\widehat{\sigma}_k^2}{\tau^2 + \widehat{\sigma}_k^2}$ as an estimate of the

shrinkage factor $\frac{\widehat{\sigma}_k^2}{\tau^2 + \widehat{\sigma}_k^2}$.

The empirical Bayes framework sketched above was initially proposed by Efron and Morris (1973; 1975) to interpret the James-Stein rule for estimating multivariate normal means. Indeed, Stein (1956) and James and Stein (1961) discovered that for simultaneous estimation of

unrelated normal means, the usual MLE (i.e., Y_k 's) can be inadmissible and dominated by a shrinkage estimator similar in form to the empirical Bayes estimator (7). On the other hand, the empirical Bayes method closely parallels the notion of best linear unbiased prediction (BLUP) in random effects models (Robinson 1991). Specifically, when both the prior variance τ^2 and the sampling variances σ_k^2 are known, it can be shown that the following statistic minimizes the mean squared error between θ_k and any unbiased estimator of θ_k that is linear in the Y_k 's (Harville 1976):

$$\hat{\theta}_k^{\text{BLUP}} = \hat{\mu} + \left(1 - \frac{\sigma_k^2}{\tau^2 + \sigma_k^2}\right)(Y_k - \hat{\mu}). \quad (8)$$

Here $\hat{\mu} = \sum_{k=1}^K w_k Y_k / \sum_{k=1}^K w_k$ is the minimum variance unbiased estimator (MVUE) of μ , where $w_k = 1/(\tau^2 + \sigma_k^2)$. Replacing the variance components τ^2 and σ_k^2 with their estimates would yield the *empirical best linear unbiased predictor* (EBLUP) of θ_k , which coincides with the empirical Bayes estimator (7) except for the lack of the multiplying constant $\frac{K-3}{K-1}$.

While the theoretical work by James and Stein (1961) demonstrates the advantage of shrinkage in a fixed effects world, the concepts of BLUP and EBLUP justify the empirical Bayes estimator through a random effects formulation. From either perspective, the key idea is to reduce the influence of sampling variability by “borrowing strength” from other observations (as reflected in $\hat{\mu}$). Since the shrinkage factor roughly equals the ratio of the sampling variance σ_k^2 to the overall variance of Y_k —that is, $\tau^2 + \sigma_k^2$ —the shrinkage rule may be interpreted as “purging” sampling errors from the estimation of true parameters. This procedure can be highly effective when sampling uncertainty is substantial relative to the true variation among the parameters of interest. As illustrated by Efron and Morris (1975), given data from the first 45 bats of 18 major league baseball players in the 1970 season, the shrinkage approach performs much better than

the MLE in predicting their future batting averages. More recently, Savitz and Raudenbush (2009) showed that similar types of shrinkage estimators can improve the precision and predictive validity of econometric measures in neighborhood studies. Considering that observed log odds ratios frequently suffer from large sampling errors, we expect that the shrinkage approach can significantly enhance the estimation precision of log odds ratios by pooling data from multiple mobility tables.

Meanwhile, we notice from equation (7) that the degree of shrinkage is higher for observations with larger sampling variances. This relationship is intuitive because the need for “borrowing strength” should be stronger for relatively imprecise estimates. Differences in the degree of shrinkage, moreover, can alter the rank order of the estimates; that is, the shrinkage estimates may rank the population log odds ratios differently from the observed log odds ratios. Efron and Morris (1975) noted that the empirical Bayes method typically outperforms MLE in ordering the true values. Therefore, besides improving the estimation precision of individual log odds ratios, the shrinkage approach can also enhance the accuracy of cross-table comparisons.

Estimation, Inference, and Implementation

To empirically estimate μ and τ^2 , a natural idea is to derive their MLE based on the joint marginal distribution

$$Y_k \overset{indep}{\sim} N(\mu, \tau^2 + \widehat{\sigma}_k^2).$$

Unfortunately, the likelihood equation in this case defies an analytical solution. I now describe an alternative approach proposed by Carter and Rolph (1974), one that is closely related to the procedures used in Fay and Herriot (1979), Morris (1983), and Sidik and Jonkman (2005). As mentioned above, when τ^2 is known, the minimum variance unbiased estimator of μ is given by the weighted average of the Y_k 's

$$\hat{\mu}(\tau^2) = \frac{\sum_{k=1}^K w_k(\tau^2) Y_k}{\sum_{k=1}^K w_k(\tau^2)},$$

where the weights are

$$w_k(\tau^2) = \frac{1}{\tau^2 + \sigma_k^2}.$$

Here $w_k(\tau^2)$ and $\hat{\mu}(\tau^2)$ highlight their dependence on τ^2 . Meanwhile, we observe that the weighted sum of squared deviations of the Y_k 's follows a chi-square distribution with $K - 1$ degrees of freedom—that is,

$$\sum_{k=1}^K w_k(\tau^2) (Y_k - \hat{\mu}(\tau^2))^2 \sim \chi_{K-1}^2.$$

Thus we have

$$E \left[\sum_{k=1}^K w_k(\tau^2) (Y_k - \hat{\mu}(\tau^2))^2 \right] = K - 1.$$

Carter and Rolph (1974) suggested that τ^2 be estimated as the unique positive solution that satisfies

$$\sum_{k=1}^K w_k(\widehat{\tau^2}) (Y_k - \hat{\mu}(\widehat{\tau^2}))^2 = K - 1.$$

In the case where no positive solution exists, $\widehat{\tau^2}$ is set to be zero. To solve the above equation, a simple Newton-Raphson procedure has been described in Fay and Herriot (1979:276), which typically converges in fewer than ten iterations. With the converged value of $\widehat{\tau^2}$, the prior mean μ is estimated accordingly as $\hat{\mu}(\widehat{\tau^2})$. By plugging $\hat{\mu}$ and $\widehat{\tau^2}$ into equation (7), we obtain the empirical Bayes estimates of the unknown θ_k 's.

To fully assess the uncertainty of the empirical Bayes estimator (7), we must take into account the estimation of μ , τ^2 , and σ_k^2 's. To avoid analytical challenges, I now consider a naive estimator of the standard error of $\hat{\theta}_k^{EB}$ that treats the variance estimates $\widehat{\tau^2}$ and $\widehat{\sigma}_k^2$'s as the true

underlying parameters. Denoting by B_k the shrinkage factor $\frac{(K-3)\widehat{\sigma}_k^2}{(K-1)(\widehat{\tau}^2 + \widehat{\sigma}_k^2)}$ in equation (7), the

mean squared error between $\widehat{\theta}_k^{EB}$ and θ_k can be written as

$$\begin{aligned} E(\widehat{\theta}_k^{EB} - \theta_k)^2 &= E[(1 - B_k)Y_k + B_k\hat{\mu} - \theta_k]^2 \\ &= E[(1 - B_k)(Y_k - \theta_k) + B_k(\hat{\mu} - \theta_k)]^2 \\ &= (1 - B_k)\widehat{\sigma}_k^2 + 2(1 - B_k)B_k\left(\frac{w_k}{\Sigma w_k}\right)\widehat{\sigma}_k^2 + B_k^2\left(\widehat{\tau}^2 - \frac{2w_k\widehat{\tau}^2}{\Sigma w_k} + \frac{1}{\Sigma w_k}\right). \end{aligned}$$

Therefore, by taking the square root of the right-hand side, we obtain an estimator of the standard error of $\widehat{\theta}_k^{EB}$. Alternatively, we can fit random effects models using standard software for meta-analysis (such as the metafor package in R; see Viechtbauer 2010) and extract estimates of BLUPs and their standard errors, which should be very close to the empirical Bayes estimates.

The standard error derived above tends to underestimate the uncertainty of $\widehat{\theta}_k^{EB}$'s because it ignores the estimation of τ^2 and σ_k^2 's. A fully Bayesian approach, as noted by Raudenbush and Bryk (2002), will take account of the estimation uncertainty of μ , τ^2 , and θ_k 's simultaneously. To build a full Bayes model, we may supply the hyperparameters μ and τ^2 with noninformative priors (for example, by setting a normal prior with a variance of 10^6 for μ and a uniform prior from 0 to 10^4 for τ^2). Such a model can be easily implemented using standard MCMC software such as BUGS. Later I will illustrate both the empirical Bayes and the full Bayes methods using a set of 16 mobility tables.

Usual Estimator Versus Shrinkage Estimator in Simulation

We now turn our attention back to the setting of K 2×2 mobility tables, each representing a country. As noted earlier, the shrinkage factor is decided by the sampling variance of the

observed log odds ratio relative to the true variation in log odds ratio among the K countries. The influence of shrinkage, therefore, should be stronger when *the true variation in mobility* is relatively small compared with sampling errors. On the other hand, since sampling variance typically differs from country to country, the shrinkage estimates may exhibit a different rank order from that of the usual estimates. Clearly, the extent of this discrepancy should depend on *the extent of variation in sample size* among these countries. In this subsection, I use numerical simulation to examine how potential advantages of the shrinkage approach vary along these two dimensions. I compare the performance between the usual estimator (1) and the shrinkage estimator (7) in two aspects: (1) total squared error, and (2) correlation with the true log odds ratios.

Let us consider 100 2×2 mobility tables depicting, say, intergenerational mobility between white-collar and blue-collar occupations in 100 countries.¹⁹ Following the convention in mobility table analysis, I represent father's occupation in rows and son's occupation in columns. In this simulation, I assume that these countries are at the same stage of industrial development such that 40% of the sample is from white-collar origin in all of the 100 mobility tables. In other words, the row marginal distribution is fixed to be (0.4, 0.6). Despite the homogeneous origin distribution, I allow these countries to vary in the extent of relative mobility as measured by the log odds ratio. In particular, I create three scenarios in which the true variation in log odds ratio among these countries is small, medium, and large. Suppose that a son's occupation given a father's occupation follows a binomial distribution, and use $p_{1|1}^k$ and $p_{1|2}^k$ to denote the probabilities of working in a white-collar occupation respectively for a person from white-collar origin and for a person from blue-collar origin in country k . I assume that $p_{1|1}^k$ and $p_{1|2}^k$ are

¹⁹ For convenience, the agricultural sector is omitted in this simulation study.

independently and uniformly distributed around 0.7 and 0.3, respectively, which means that the probability of being immobile (i.e., staying in the main diagonal of the table) is around 0.7 for both white-collar and blue-collar occupations. I then construct the three scenarios by letting the range of the two uniform distributions be 0.08, 0.16, and 0.24.²⁰ In other words, $p_{1|1}^k$ and $p_{1|2}^k$ are independently drawn from the following two distributions:

$$p_{1|1}^k \stackrel{i.i.d.}{\sim} \text{Uniform}(0.7 - 0.04 * \alpha, 0.7 + 0.04 * \alpha), \quad k = 1, 2, \dots, 100, \quad (9)$$

$$p_{1|2}^k \stackrel{i.i.d.}{\sim} \text{Uniform}(0.3 - 0.04 * \alpha, 0.3 + 0.04 * \alpha), \quad k = 1, 2, \dots, 100, \quad (10)$$

where the parameter α , which may take 1, 2, and 3, is used to generate settings in which the true variation in log odds ratio is small, medium, and large.

The three scenarios above differ in the true variation of log odds ratio and thus in the estimate of τ^2 in equation (7), which will affect the shrinkage factor uniformly for all countries. As mentioned earlier, the contrasts between the shrinkage estimator and the usual estimator may also depend on the amount of variation in sample size among the mobility tables, which shapes the variation among the $\widehat{\sigma}_k^2$'s. Therefore, I also compare the performance between the two estimators as variation in sample size changes from very small to very large. Specifically, I assume that the sample size follows a log-uniform distribution as below:

$$\log n_{++k} \stackrel{i.i.d.}{\sim} \text{Uniform}(\log 800 * 2^\beta, \log 1250 * 2^\beta), \quad k = 1, 2, \dots, 100, \quad (11)$$

where n_{++k} denotes the sample size for country k . I vary the parameter β from 0 to 4 with a step size of 1, thereby generating five scenarios with a gradual change in the variation of sample size while fixing the median sample size among these countries to be around 1,000. For example,

²⁰ The parameters for the row marginal distribution, the average transition probabilities, and the ranges of the transition probabilities, are all chosen based on the empirical mobility tables for 16 countries collected by Hazelrigg and Garnier (1976).

sample size will range between 800 and 1,250 when β takes 0 but range between 50 and 20,000 when β takes 4.

In this simulation, I exhaust all possible combinations of α and β , resulting in $3 \times 5 = 15$ scenarios. For each of these scenarios, I generated the 100 mobility tables in the following steps:

1. For each table k , generate the sample size using $n_{++k} = \lfloor \exp(M) \rfloor$, where M is a random draw from the uniform distribution (11), and $\lfloor \exp(M) \rfloor$ means taking the integer closest to $\exp(M)$.
2. Calculate the row marginals (n_{1+k}, n_{2+k}) by assigning 40% of the sample size n_{++k} to the first category (i.e., white-collar).
3. Generate the transition probabilities $p_{1|1}^k$ and $p_{1|2}^k$ using the uniform distributions (9) and (10).
4. Create the mobility table $(n_{11k}, n_{12k}, n_{21k}, n_{22k})$ using binomial draws for each row—that is, binomial $(n_{1+k}, p_{1|1}^k)$ for the first row and binomial $(n_{2+k}, p_{1|2}^k)$ for the second row.

Given the simulated tables, I applied both the usual estimator (1) and the empirical Bayes estimator (7) to estimate the log odds ratios. I then evaluated the performance of the two estimators using two criteria: (1) total squared error, i.e., $\sum_{k=1}^{100} (\hat{\theta}_k - \theta_k)^2$, and (2) Pearson's correlation coefficient (among the 100 countries)—that is, $\text{Cor}(\hat{\theta}_k, \theta_k)$. To smooth random fluctuations, I averaged these two measures over 500 iterations of the above procedures (data generation, estimation, and evaluation) for each of the 15 scenarios.

Figure IV.1 presents the results, with panel (a) for total squared errors and panel (b) for the correlation coefficients. In both panels, I represent the usual estimator in squares and the

shrinkage estimator in triangles. The three scenarios in which the true variation in log odds ratio is small, medium, and large are represented respectively by solid, dashed, and dotted lines. First, we observe that in virtually all of the 15 scenarios, the shrinkage estimator exhibits lower total squared errors and higher correlations with the true values than does the usual estimator. This is consistent with theoretical results on joint estimation of normal means as discussed by Efron and Morris (1973; 1975). Second, as shown by both panels, the benefits of the shrinkage estimator are greater when the true variation in log odds ratio is smaller. This relationship is intuitive because the shrinkage approach is essentially pooling information across cases, which should be more effective when these cases are more similar to each other. We also note that for both estimators, the correlation with the true values increases as the true variation in log odds ratio increases. This is because when the true differences are larger, they are less likely to be confounded by sampling fluctuations and thus more likely to be detected from the data. Finally, reading along the X -axis, we find that the advantage of the shrinkage estimator becomes more pronounced as the variation in sample size increases. In fact, both estimators perform worse when there is greater variation in sample size. However, the shrinkage estimator is far more robust than the usual estimator in this aspect. For instance, in the case where the true variation in log odds ratio is small (solid lines), the correlation between the usual estimates and the true values declines from above 0.7 to below 0.5 as the variation in sample size changes from very small to very large, whereas the correlation between the shrinkage estimates and the true values stays roughly unchanged (around 0.71) regardless of the variation in sample size.

To sum up, this simulation study suggests that the shrinkage estimator almost always outperforms the usual estimator in joint estimation of multiple log odds ratios, either in terms of total squared error or in terms of the correlation with the true values. Moreover, the advantage of

the shrinkage estimator is more pronounced when there is less variation in the true log odds ratio or more variation in sample size. In particular, the higher correlations with the true values exhibited by the shrinkage estimator reveal its great potential for enhancing the accuracy of cross-table comparisons.

Shrinkage at Work: An Example

I now apply the shrinkage method to the mobility data assembled by Hazelrigg and Garnier (1976), which provide 3×3 classifications of son's occupation by father's occupation for 16 countries in the 1960s and 1970s (henceforth referred to as HG-16). The data are displayed in Table IV.1. In each of the 16 tables, occupation is categorized as white collar, blue collar, or farm. Let us consider two sets of log odds ratios that are of particular substantive interest: (1) the log odds ratio pertaining to the 2×2 subtable of white collar and blue collar workers, and (2) the log odds ratio pertaining to the 2×2 subtable of blue collar workers and farmers. We may perceive these two log odds ratios as measuring the strengths of class boundaries between white collar and blue collar and between blue collar and farm. For each measure, I contrast the observed log odds ratios with both the empirical Bayes estimates and the full Bayes estimates. To generate the full Bayes estimates, I ran five independent Markov chains, each containing 4,000 iterations, and retained the last 2,000 vectors from each run. The point estimates and the standard errors of the log odds ratios were estimated respectively as the posterior means and the posterior standard deviations.

The results are shown in Table IV.2. On the one hand, we observe that for countries with very large sample sizes, such as Spain, United States, and West Germany, both the point estimates and the standard errors are largely the same across different methods. Because within-sample precision is sufficiently high for these countries, the shrinkage factors assigned to the

observed log odds ratios are almost zero. The shrinkage estimates, therefore, closely resemble the MLE in both location and precision. On the other hand, for relatively sparse tables, such as Finland, Norway, and Sweden, both the point estimates and the standard errors are markedly changed under the shrinkage methods. However, the empirical Bayes approach and the full Bayes approach yield essentially identical point estimates, although the latter gives slightly larger standard errors as it incorporates the uncertainty of the prior variance τ^2 . Overall, shrinkage estimates based on either approach are more precise than the usual estimates.

To demonstrate the effects of shrinkage, I visualize the contrasts between the observed log odds ratios and the empirical Bayes estimates in Figure IV.2, where 9 of the 16 countries are marked for illustration: Belgium, France, Hungary, Italy, Spain, United States, West Malaysia, Norway, and Sweden. Panel (a) shows the log odds ratio between white collar and blue collar. First, we find that most of the cross-country differences are consistent between the two sets of estimates: For example, according to either estimator, Spain and West Malaysia are respectively the least mobile (i.e., with the highest log odds ratio) and the most mobile (i.e., with the lowest log odds ratio) among the nine countries. However, because the observed log odds ratios differ in sampling precision, the shrinkage estimator implies a slightly different rank order among these countries. In particular, Norway is more mobile than the United States according to the usual estimator (i.e., the observed odds ratio) but less mobile than the United States according to the shrinkage estimator. In other words, the empirical Bayes model suggests that the higher mobility of Norway exhibited by the raw data is simply due to its larger sampling variance, not because

the barrier between white collar and blue collar jobs is more permeable in Norway than in the United States.²¹

Panel (b) demonstrates the effects of shrinkage for the log odds ratio between blue collar and farm. Overall, these estimates are much higher than the estimates in the left panel, indicating that the barrier between these two classes is much harder to cross than the barrier between white collar and blue collar jobs. Similar to the left panel, the rankings among the nine countries are not much altered under the shrinkage approach, except that Norway is again “shrunk toward the mean.” We also find that the influence of shrinkage is the most pronounced for Belgium, which is markedly less mobile than France according to the observed log odds ratio but closely resembles France in their shrinkage estimates. This is clearly related to the sparse cell of (blue collar, farm) in the Belgian table (see again Table IV.1).

Adjusted Estimation of the Altham Index

For mobility tables with more than two categories, we can use the shrinkage estimator (7) to calculate summary measures of association that are based on aggregations of log odds ratios. In this section, I construct an adjusted estimator of the Altham index, an aggregate measure of association that has been recently employed for studying intergenerational occupational mobility (Ferrie 2005; Long and Ferrie 2007, 2013). Results from a set of calibrated simulations suggest that using shrinkage estimates of log odds ratios can substantially improve the estimation precision of the Altham index.

²¹ If we calculate the z-score for the difference in observed log odds ratio between Norway and the U.S., we will find that it is not statistically significant.

An Adjusted Estimator of the Altham Index

To assess the total amount of association embodied in a two-way contingency table, Altham (1970) proposed a number of measures that are based on aggregations of log odds ratios. One such measure is identical to the Euclidean distance between the full sets of log odds ratios in two $I \times J$ tables P and Q —that is,

$$d(P, Q) = \left[\sum_{i=1}^I \sum_{j=1}^J \sum_{l=1}^I \sum_{m=1}^J \left| \log \frac{p_{ij}p_{lm}}{p_{im}p_{lj}} - \log \frac{q_{ij}q_{lm}}{q_{im}q_{lj}} \right|^2 \right]^{1/2},$$

where p_{ij} and q_{ij} denote the probabilities associated with the cell (i, j) in table P and table Q .

While the metric $d(P, Q)$ gauges the distance between the row-column associations in tables P and Q , it does not tell us in which table the rows and the columns are more closely associated. To answer this question, we can compare $d(P, J)$ with $d(Q, J)$, where J denotes a contingency table in which the rows and columns are completely independent. Since all of the log odds ratios are zero in an independent table, we have

$$d(P, J) = \left[\sum_{i=1}^I \sum_{j=1}^J \sum_{l=1}^I \sum_{m=1}^J \left| \log \frac{p_{ij}p_{lm}}{p_{im}p_{lj}} \right|^2 \right]^{1/2}. \quad (12)$$

We can see that $d(P, J)$ is the square root of the sum of all squared log odds ratios in table P . A larger value of $d(P, J)$ indicates a stronger association between the rows and columns. Hence, when P is a mobility table, a larger $d(P, J)$ corresponds to a more rigid class regime. Although this approach to comparing mobility tables is lesser-known than log-linear models in comparative stratification research, it has been recently employed by economic historians to study long-term trends in occupational mobility in Great Britain and the United States (Ferrie 2005; Long and Ferrie 2007, 2013). From here on, I use “the Altham index” to mean $d(P, J)$ for a contingency table P .

Now suppose we have a set of $I \times I$ mobility tables M_1, M_2, \dots, M_K for K countries. For each country k , we can directly calculate the Altham index by substituting the observed log odds ratios:

$$\hat{d}^{\text{Direct}}(M_k, J) = \left[\sum_{i=1}^I \sum_{j=1}^J \sum_{l=1}^I \sum_{m=1}^J \left| \log \frac{n_{ijk} n_{lmk}}{n_{imk} n_{ljk}} \right|^2 \right]^{1/2}, \quad k = 1, 2, \dots, K, \quad (13)$$

where n_{ijk} denotes the observed frequency associated with the cell (i, j) in table k .²² On the other hand, we can use the shrinkage estimator of the log odds ratio for each row-column combination (i, j, l, m) , yielding an adjusted estimator of the Altham index:

$$\hat{d}^{\text{Adjusted}}(M_k, J) = \left[\sum_{i=1}^I \sum_{j=1}^J \sum_{l=1}^I \sum_{m=1}^J \left| \hat{\theta}_{(i,j,l,m),k}^{EB} \right|^2 \right]^{1/2}, \quad k = 1, 2, \dots, K, \quad (14)$$

where $\hat{\theta}_{(i,j,l,m),k}^{EB}$ denotes the shrinkage estimator (7) of the log odds ratio $\log \frac{p_{ij} p_{lm}}{p_{im} p_{lj}}$ in table k .

Since the Altham index is not a linear function of the log odds ratios, the adjusted estimator (14) cannot be expressed as a weighted average between the direct estimator (13) and a common mean as in equation (7). However, as we will see, the key effect of this adjustment is also “pulling” the direct estimates toward the middle, the extent of which depends on sample sizes of the corresponding tables.

Direct Estimator Versus Adjusted Estimator in Simulation

Below, I use numerical simulation to evaluate the performance of the direct estimator (13) and the adjusted estimator (14) for the Altham index. As in the case of the log odds ratio, I compare them in two aspects: (1) total squared error, and (2) correlation with the true values. To mimic mobility regimes in the real world, I use HG-16 to motivate my simulation setup. First, I fitted

²² As before, when any of the four cells is zero, one half is added to all of the four cells before calculation.

the 16 3×3 mobility tables using four log-linear (or log-multiplicative) models: (1) quasi-perfect mobility, (2) uniform inheritance, (3) perfect blue-collar mobility, and (4) the Unidiff model with full row-column interaction. These models have been proposed by Grusky and Hauser (1984) (a,b,c) and Xie (1992) (d) to compare mobility regimes of the 16 countries.²³ I then treated the estimated parameters as the true parameters, yielding four data-generating models—that is, four simulation setups. For each of the four setups, I generated 1,000 independent samples of the 16 tables, and, for each sample, obtained the direct and the adjusted estimates of the Altham index. With the “true” Altham indices readily available from the model parameters, I evaluated the two estimators using three criteria: (1) total squared error, (2) Pearson’s correlation with the true values, and (3) Spearman’s rank correlation with the true values. To smooth random fluctuations, each of the three measures was averaged over the 1,000 samples, thus producing the total mean squared error (total MSE) and the average correlation coefficients. The results are summarized in Table IV.3.

We first observe in this table that the adjusted estimator leads to a substantial reduction in total MSE in all of the four scenarios. For example, when data are generated from the Unidiff model, total MSE for the adjusted estimator is only about half of that for the direct estimator ($38.8/77.0=50.4\%$). Moreover, the adjusted estimates compete well with the direct estimates in correlating with the true Altham indices. Specifically, the adjusted estimator (on average) brings an increase in Pearson’s correlation in all of the four scenarios and an increase in Spearman’s rank correlation in two of the four scenarios. Therefore, the shrinkage-based method for

²³ Models (a), (b), (c) correspond respectively to models A2, A3, A4 in Grusky and Hauser (1984, p.389); model (d) corresponds to model FI_x in Xie (1992, p.390).

calculating the Altham index not only yields more precise individual estimates, but may also enhance the accuracy of cross-table comparisons in the overall degree of association.

An Illustration Using HG-16

I now apply both estimators of the Altham index to the real data in HG-16. The results are shown in Figure IV.3(a), where the same nine countries as in the previous section are highlighted for illustration. Clearly, with the shrinkage estimates of log odds ratios, the Altham index tends to be shrunk toward the middle, yet the degree of shrinkage varies considerably from country to country. For example, the adjusted estimate is very similar to the direct estimate for France, but the estimate for Sweden is heavily altered by the adjustment. According to the direct estimates, Sweden ranks as the least mobile (i.e., with the highest Altham index) among the 16 countries; but by the adjusted estimates, Sweden stands right in the middle, more mobile than Hungary, France, Belgium, Italy, and Spain. Such a sharp contrast suggests that the high (direct) estimate of the Altham index for Sweden is primarily a result of large sampling errors for some of the log odds ratios in the Swedish data. As was shown in Table IV.1, the cell (white collar, farm) of the Swedish table contains no observation, which may have led to an incredibly high estimate of the Altham index.

We can also evaluate the Altham index for a subset of the mobility table. Figure IV.3(b) presents the results for the same set of tables with the farm-farm cells excluded. The uniqueness of the farm-farm cell has been emphasized by Xie and Killewald (2013), who argued that the extremely persistent degree of inheritance from farming among farmers (regardless of historical contexts) challenges the utility of odds-ratio-based measures for comparing mobility regimes with very different levels of industrialization. Hence, calculating the Altham index without the farm-farm cell serves as a sensitivity check on the results in panel 3(a). Two findings emerge

from this analysis. First, compared with panel (a), we find that the exclusion of the farm-farm cell leads to significant changes in the positions of these countries along the mobility spectrum. For instance, when the full tables are analyzed, France and Hungary are fairly close to each other, both ranking among the least mobile regimes; when the farm-farm cells are excluded, France appears to be one of the most mobile countries, whereas Hungary stands out as the single most immobile regime, with an Altham index far higher than those of the others. Second, although the adjusted estimates have the same rank order as the direct estimates for the nine countries marked here, they differ substantially in relative positions. For example, according to the direct estimates (without the farm-farm cell), Norway and Sweden are far apart, one very close to West Malaysia and the other only slightly lower than Spain; however, with the shrinkage-based adjustment, these two Nordic countries are much more similar, with their Altham indices closer to France and the United States than to West Malaysia and Spain.

Shrinking Toward Convergence: Comparing the Altham Index with the Unidiff Model

Although the Altham index provides a simple summary measure of the row-column association for a mobility table, log-linear modeling has been far more popular among sociological studies on intergenerational class mobility, in part due to its flexibility for accommodating fine-grained theoretical hypotheses (e.g., Erikson and Goldthorpe 1987; Hout 1984, 1988; Yamaguchi 1987). Among a plethora of log-linear and log-multiplicative models that have been proposed for studying mobility tables, the Unidiff model (also known as the log-multiplicative layer effect model) is particularly recognized for its ability to provide a single parameter that captures cross-table differences in social fluidity (Xie 1992; Erikson and Goldthorpe 1992). Hence, the Altham index and the Unidiff model constitute two different approaches to making overall comparisons between mobility tables. In this section, I first establish a theoretical equivalence between these

two approaches in the ideal case where the Unidiff model is the true data-generating model. Then, using two real data sets, I show that the adjusted estimates of the Altham index agree more closely with the layer effects estimated under the Unidiff model than do direct estimates of the Altham index.

The Unidiff Model, the Layer Effect, and the Altham Index

As in the preceding section, let us consider a set of $I \times I$ mobility tables M_1, M_2, \dots, M_k for K countries. In a log-linear analysis, these tables are typically treated as a three-way table with I rows, I columns, and K layers. Denoting by F_{ijk} the expected frequency in the i th row, the j th column, and the k th layer (i.e., the k th country), the saturated log-linear model can be written as

$$\log F_{ijk} = \mu + \mu_i^R + \mu_j^C + \mu_k^L + \mu_{ik}^{RL} + \mu_{jk}^{CL} + \mu_{ij}^{RC} + \mu_{ijk}^{RCL}.$$

In this equation, the first six terms are used to saturate the marginal distributions of both the origin and the destination in each country, while the last two terms, μ_{ij}^{RC} and μ_{ijk}^{RCL} , capture variations in the origin-destination association across countries. However, since the saturated model exhausts all degrees of freedom, it would severely overfit the data. In practice, the researcher often wants to specify μ_{ij}^{RC} and μ_{ijk}^{RCL} in a parsimonious fashion. The Unidiff model, in particular, assumes that these countries share a common pattern of association between origin and destination while allowing the strength of association to vary across countries. As a result, the model can be written as

$$\log F_{ijk} = \mu + \mu_i^R + \mu_j^C + \mu_k^L + \mu_{ik}^{RL} + \mu_{jk}^{CL} + \psi_{ij}\phi_k. \quad (15)$$

Here, the parameter ψ_{ij} characterizes the common pattern of association, and the parameter ϕ_k , which is called the “layer effect,” identifies the relative position of country k along the mobility spectrum.

According to equation (15), the expected log odds ratio associated with the row-column combination (i, j, l, m) in table k can be calculated as

$$\theta_{(i,j,l,m),k} = \log F_{ijk} - \log F_{imk} - \log F_{ljk} + \log F_{lmk} = \theta_{i,j,l,m}^* \phi_k, \quad (16)$$

where $\theta_{i,j,l,m}^* = \psi_{ij} - \psi_{im} - \psi_{lj} + \psi_{lm}$. Therefore, under the Unidiff model, any log odds ratio in a given table is the product of a common log odds ratio $\theta_{i,j,l,m}^*$ and the layer effect ϕ_k . Clearly, a greater value of ϕ_k implies a lower degree of social fluidity. Substituting the above expression into equation (12), the Altham index becomes

$$d(M_k, J) = \left[\sum_{i,j,l,m} |\theta_{(i,j,l,m),k}|^2 \right]^{1/2} = \left[\sum_{i,j,l,m} |\theta_{i,j,l,m}^*|^2 \right]^{1/2} \phi_k. \quad (17)$$

Since the term $\left[\sum_{i,j,l,m} |\theta_{i,j,l,m}^*|^2 \right]^{1/2}$ does not depend on k , the Altham index $d(M_k, J)$ is directly proportional to the layer effect ϕ_k . In other words, these two measures of association are equivalent under the Unidiff model.

Real mobility data, however, may fail to support the assumptions of the Unidiff model. For example, according to the likelihood ratio test, the Unidiff model fits poorly for HG-16 (Xie 1992:390). In such cases, we may conclude that different mobility regimes exhibit different patterns of relative mobility, and proceed to develop more flexible models, such as the regression-type models proposed by Goodman and Hout (1998), to capture the nuances of cross-table differences. Nonetheless, tempted by such questions as “Overall, is country A more mobile than country B?” the researcher may still be interested in reducing subtle, multidimensional differences to simple, one-dimensional contrasts. In this regard, the Unidiff model and the Altham index constitute two reasonable yet distinct approaches. A natural question, then, is whether these two approaches would yield concordant results. Since the layer effect and the Altham index are equivalent when the Unidiff model is true, we would expect that they produce

more similar results when data are more congruent with the Unidiff model. On the other hand, given the advantages of the adjusted estimator over the direct estimator for the Altham index, it is reasonable to conjecture that the adjusted estimator agrees more closely than the direct estimator with results from the Unidiff model. Below, I use two sets of real mobility tables to test these two hypotheses.

Shrinking Toward Convergence: Evidence from Two Data Sets

I apply both estimators of the Altham index, along with the Unidiff model, to two data sets: (1) HG-16—that is, the 16 3×3 mobility tables assembled by Hazelrigg and Garnier (1976), and (2) a collection of 149 6×6 mobility tables from 35 countries assembled by Ganzeboom, Luijkx, and Treiman (1989), henceforth GLT-149. While occupation in HG-16 is crudely classified as white collar, blue collar, and farm, GLT-149 adopts the six-category version of the EGP class scheme: the service class (I+II), routine nonmanual workers (III), petty bourgeoisie (IVa+b), farmers and agricultural laborers (IVc+VIIb), skilled manual workers (V+VI), and unskilled manual workers (VIIa).

To assess the extent to which different estimators of the Altham index accord with the layer effects estimated under the Unidiff model, I use Spearman's rank correlation as well as the Pearson correlation. Previous researchers analyzing HG-16 have pointed out that Hungary significantly deviates from the other 15 countries in patterns of interclass mobility (Grusky and Hauser 1984; Xie 1992). For this reason, I analyzed both the full set of HG-16 and the 15 tables excluding the Hungarian case (henceforth referred to as HG-15). The results are shown in Table IV.4. We can see that for all three data sets, the fitted layer effects $\hat{\phi}_k^{\text{Unidiff}}$ tend to correlate more strongly with the adjusted estimates of the Altham index than with the direct estimates,

especially by Spearman's rank correlation. For example, the rank correlation for GLT-149 is 0.839 between $\hat{d}^{\text{Direct}}(M_k, J)$ and $\hat{\phi}_k^{\text{Unidiff}}$ but 0.899 between $\hat{d}^{\text{Adjusted}}(M_k, J)$ and $\hat{\phi}_k^{\text{Unidiff}}$.

On the other hand, we notice that when Hungary is excluded from HG-16, both estimates of the Altham index become more aligned with the fitted layer effects. The Pearson correlation, for example, increases from 0.858 to 0.917 between $\hat{d}^{\text{Direct}}(M_k, J)$ and $\hat{\phi}_k^{\text{Unidiff}}$ and from 0.852 to 0.939 between $\hat{d}^{\text{Adjusted}}(M_k, J)$ and $\hat{\phi}_k^{\text{Unidiff}}$. These results accord well with our first hypothesis: Because Hungary contributes the lion's share to the model deviance (i.e., G^2), its exclusion considerably improves the fit between the data and the Unidiff model, thereby producing greater consistency between model-free (i.e., the Altham index) and model-based (i.e., the Unidiff model) inferences. To explore this relationship further, I examine how the above correlations change as the most poorly fitted cases are progressively excluded from the data sets. Specifically, for HG-16, I performed a stepwise elimination of Hungary, France, West Germany, the United States, and Spain—in order of decreasing G^2 under the Unidiff model—and recalculated the correlations for each subset of the 16 tables. For GLT-149, the same procedures were followed except that five tables, rather than one table, were removed at a time and the correlation coefficients were recalculated until 40 tables were deleted.

Figure IV.4 shows the results, with panel (a) for HG-16 and panel (b) for GLT-149. In both panels, I represent Pearson's correlation in solid lines and Spearman's rank correlation in dashed lines. Meanwhile, squares and triangles denote direct and adjusted estimates of the Altham index, respectively. From the four contrasts between squares and triangles, we notice that the adjusted estimates of the Altham index almost always correlate more strongly with the fitted layer effects than do the direct estimates. On the other hand, reading along the X -axis, we find that the correlation coefficients generally increase as the most poorly fitted cases are excluded

from the data sets. The upward drift, however, is more noticeable for the adjusted estimator than for the direct estimator. As a result, the gap between $\hat{d}^{\text{Direct}}(M_k, J)$ and $\hat{d}^{\text{Adjusted}}(M_k, J)$ in their correlations with $\hat{\phi}_k^{\text{Unidiff}}$ grows larger as data align more closely with the Unidiff model. For example, when the full set of GLT-149 is analyzed, the Pearson correlation between $\hat{d}^{\text{Adjusted}}(M_k, J)$ and $\hat{\phi}_k^{\text{Unidiff}}$ is 0.803, slightly lower than that between $\hat{d}^{\text{Direct}}(M_k, J)$ and $\hat{\phi}_k^{\text{Unidiff}}$ (0.817, see again Table IV.4); but when the 40 tables with the largest deviances are excluded, the adjusted estimates of Altham indices correlate much more strongly with the fitted layer effects than do the direct estimates.

In short, the above results suggest that in assessing the overall degree of social fluidity, the adjusted estimator of the Altham index accords more closely with the Unidiff model than does the direct estimator. Moreover, the contrast becomes more pronounced when data are more congruent with the Unidiff model. How do we understand these findings? First, we note that the adjusted estimator of the Altham index differs from the direct estimator only in its reliance on shrinkage estimates of the log odds ratios. As mentioned earlier, the underlying principle of the shrinkage method is to borrow information from other cases, particularly through an empirical Bayes model with a normal prior. The adjusted estimator of the Altham index, therefore, may be considered as a semiparametric method because it employs a normal Bayes model to smooth data across multiple tables but imposes no parametric constraints on the pattern of association within tables. In contrast, the direct estimator of the Altham index is fully nonparametric, involving no data smoothing either across or within tables. On the other hand, the Unidiff model stipulates that all log odds ratios are determined as a product of a common pattern of association and table-specific effects. This multiplicative specification requires the Unidiff model to pool data both across tables (for estimating ψ_{ij}) and across cells within tables (for estimating ϕ_k). Hence, in the

way that data are pooled to draw inferences, the adjusted estimator of the Altham index stands closer than the direct estimator to the Unidiff model, which probably explains why the shrinkage approach boosts convergence between a descriptive index and a parametric model in gauging social fluidity.

Summary and Discussion

Building on an empirical Bayes framework, I have proposed a shrinkage estimator of the log odds ratio for comparing mobility tables. This estimator enhances estimation precision by borrowing information across multiple tables while placing no restrictions on the pattern of association within tables. This approach stands in stark contrast to the usual MLE of the log odds ratio, which involves no data pooling either across or within tables. Numerical simulation suggests that the shrinkage estimator outperforms the usual MLE in both the total squared error and the correlation with the true values. Moreover, the benefits of the shrinkage method are greater when there is less variation among the true log odds ratios or more variation in sampling precision.

Furthermore, the shrinkage estimator of the log odds ratio can be employed to calculate the Altham index, an aggregate measure of association that has been recently adopted in comparative mobility research. Results from a set of calibrated simulations suggest that the adjusted estimator can substantially improve estimation precision while maintaining high correlations with the true values. Finally, using two real data sets, we find that the adjusted estimator of the Altham index accords more closely with the Unidiff model than does the direct estimator of the Altham index. This finding, as I have discussed, stems from the fact that both the Unidiff model and the shrinkage approach enforce information sharing across tables, albeit via apparently different mechanisms.

The shrinkage estimator (7) derives from a Bayes model where a common prior—that is, equation (4)—is assumed for all cases. This assumption can easily be relaxed to incorporate our prior knowledge about the similarities and differences between mobility regimes. In particular, we can extend the prior distribution (4) to

$$\theta_k \overset{indep}{\sim} N(\alpha + \beta^T X_k, \tau^2),$$

where X_k denotes a group of exogenous variables posited to affect the true log odds ratio. The empirical Bayes estimator (7) then becomes

$$\hat{\theta}_k^{EB} = \hat{\alpha} + \hat{\beta}^T X_k + \left[1 - \frac{(K-R-3)\hat{\sigma}_k^2}{(K-R-1)(\hat{\tau}^2 + \hat{\sigma}_k^2)}\right](Y_k - \hat{\alpha} - \hat{\beta}^T X_k),$$

where $\hat{\alpha}$ and $\hat{\beta}$ denote estimates of α and β , and R represents the dimension of X_k .²⁴ In this formulation, the usual estimate Y_k is shrunk not toward a common mean but toward the conditional mean $\hat{\alpha} + \hat{\beta}^T X_k$. For example, if we assume that economic development promotes social mobility, as the “thesis of industrialism” suggests (Treiman 1970), X_k could be a measure of the level of industrialization in country k . In this case, the shrinkage estimator borrows information not uniformly from all countries but mainly from countries at similar levels of industrialization. Note that if the number of tables K far exceeds the number of predictors R , the adjustment factor $\frac{K-R-3}{K-R-1}$ will be close to one and the empirical Bayes estimates can be approximated by EBLUPs from mixed-effects meta-analysis of log odds ratios (see Viechtbauer [2010] for a guide to implementation).

For evaluating the overall degree of social fluidity, the Unidiff model and the Altham index constitute two valid yet distinctive approaches. The Unidiff model stipulates that all log

²⁴ The adjustment factor changes from $\frac{K-3}{K-1}$ to $\frac{K-R-3}{K-R-1}$ because R additional degrees of freedom are used to estimate the hyper-parameters. See Morris (1983) for a more technical discussion.

odds ratios are determined multiplicatively by a common pattern of association and layer-specific effects. This is a flexible but nontrivial assumption. Not only does it require that different log odds ratios within a table are of the same relative magnitudes in all mobility regimes, but it also means that the rank order among mobility regimes does not depend on which log odds ratio is being examined. For example, a Unidiff model for GH-16 would imply that the two sets of log odds ratios in Figure IV.2 exhibit the same relative positions in the two panels, which is obviously at odds with the data. The Unidiff model, therefore, may incur a model specification bias if the true mobility regimes being compared do not comport with the “common-pattern” assumption. In contrast, the Altham index is fully nonparametric, thus being exempt from any type of model specification bias. For the same reason, however, direct calculation of the Altham index is susceptible to large sampling errors, especially for sparse tables. The shrinkage approach presented in this paper—which exploits a parametric Bayes model to “borrow strength” across tables but remains model-free within tables—serves as an eclectic formula for comparing mobility regimes, striking a balance between sampling variance and model specification bias. Clearly, this approach is applicable not only to comparative mobility analysis but to any area of research that calls for comparisons of multiple two-way contingency tables.

Figure IV.1 Usual estimator versus empirical Bayes estimator of the log odds ratio in total squared error (a) and Pearson's correlation with the true values (b) under different scenarios.

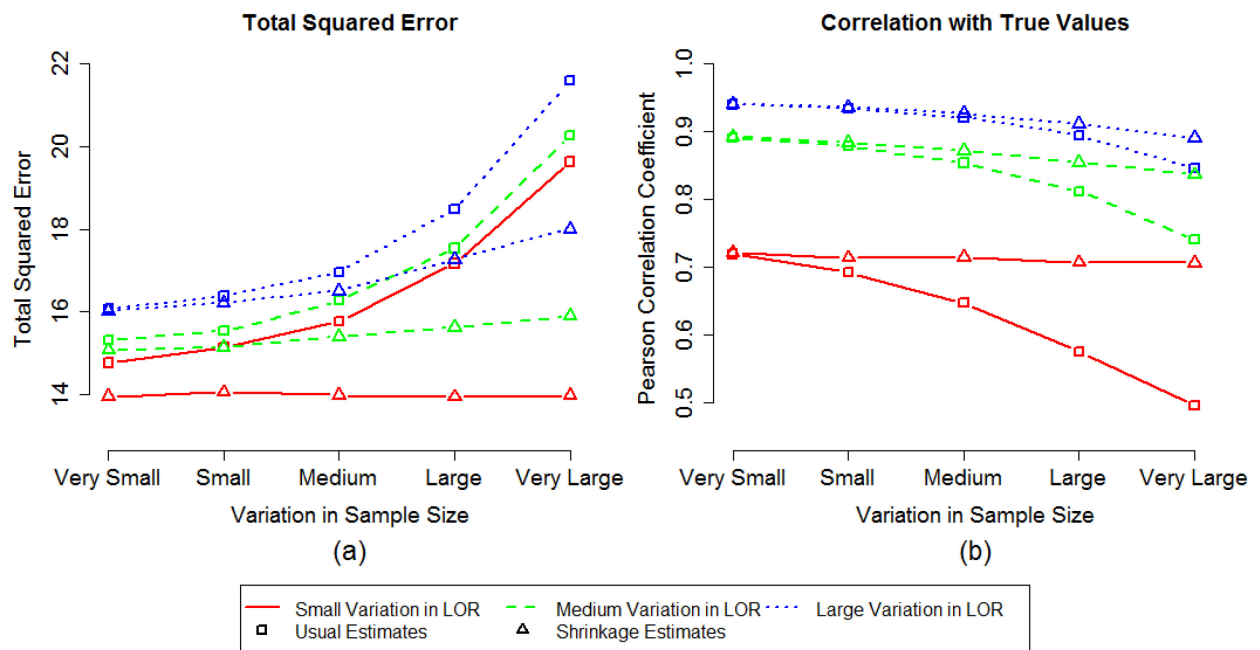


Figure IV.2 Usual estimates and shrinkage estimates for two sets of log odds ratios in HG-16.

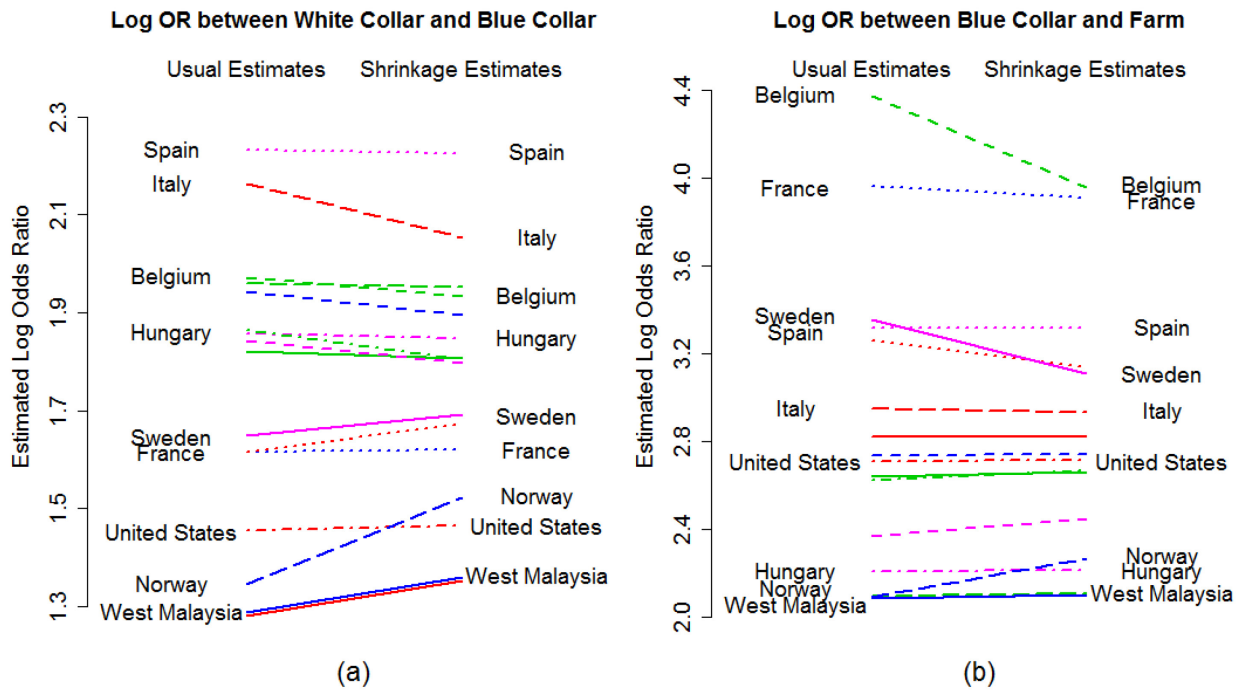


Figure IV.3 Direct estimates and adjusted estimates of the Altham index for HG-16 (a) and HG-16 without farm-farm cells (b).

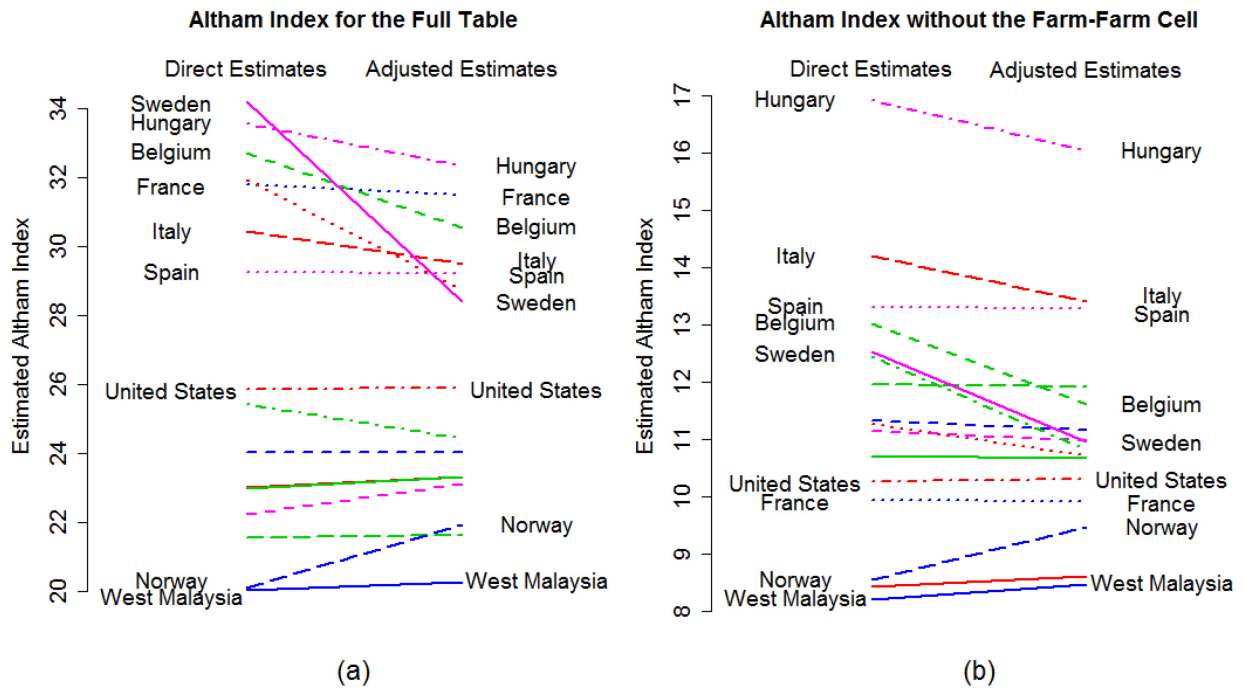


Figure IV.4 Direct estimates versus adjusted estimates of the Altham index in their correlations with ϕ_k^{\wedge} Unidiff for varying subsets of HG-16 and GLT-149.

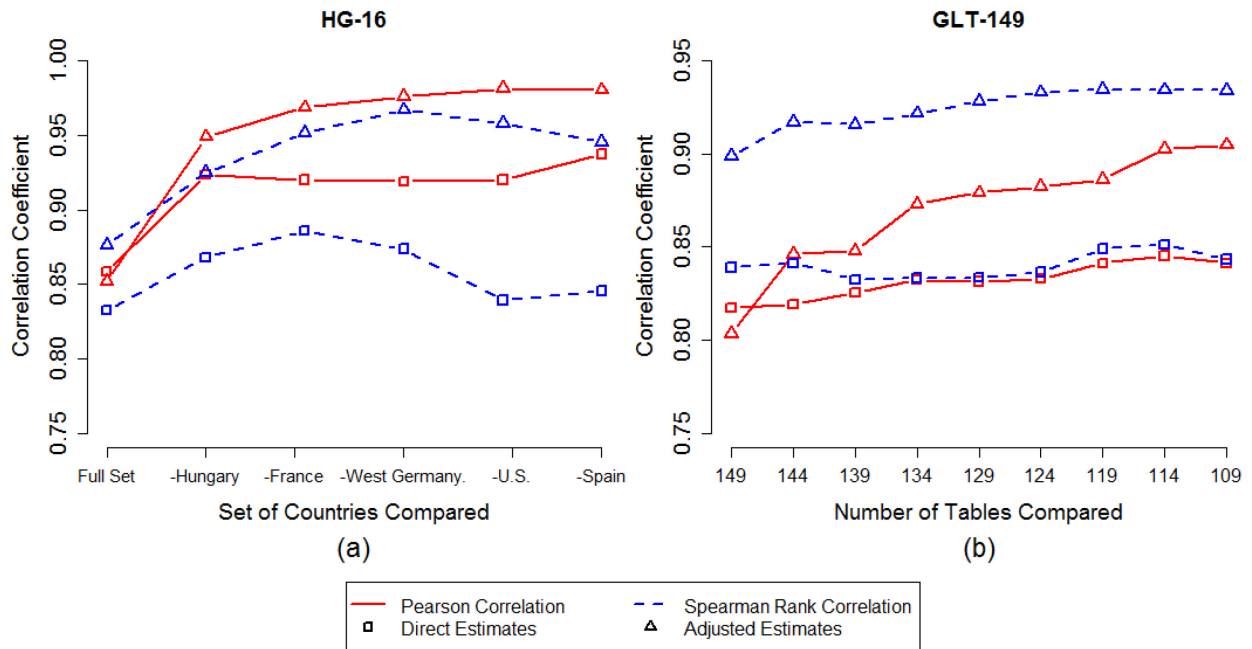


Table IV.1 Mobility Tables for 16 Countries, Father's Occupation by Son's Occupation

Australia			Belgium			France			Hungary		
292	170	29	497	100	12	2085	1047	74	479	190	14
290	608	37	300	434	7	936	2367	57	1029	2615	347
81	171	175	102	101	129	592	1255	1587	516	3110	3751
Italy			Japan			Philippines			Spain		
233	75	10	465	122	21	239	110	76	7622	2124	379
104	291	23	159	258	20	91	292	111	3495	9072	597
71	212	320	285	307	333	317	527	3098	4597	8173	14833
United States			West Germany			West Malaysia			Yugoslavia		
1650	641	34	3634	850	270	406	235	144	61	24	7
1618	2692	70	1021	1694	306	176	369	183	37	92	13
694	1648	644	1068	1310	1927	315	578	2311	77	148	223
Denmark			Finland			Norway			Sweden		
79	34	2	39	29	2	90	29	5	89	30	0
55	119	8	24	115	10	72	89	11	81	142	3
25	48	84	40	66	79	41	47	47	27	48	29

Source: Grusky and Hauser (1983:56); see also Raftery (1995:115).

Table IV.2 Point Estimates and Estimated Standard Errors for Two Sets of Log Odds Ratios in HG-16
Under Different Estimation Methods

	LOR b/w White Collar and Blue Collar			LOR b/w Blue Collar and Farm		
	Observed	Empirical Bayes	Full Bayes	Observed	Empirical Bayes	Full Bayes
Australia	1.28 (0.12)	1.35 (0.11)	1.35 (0.12)	2.82 (0.20)	2.82 (0.19)	2.82 (0.19)
Belgium	1.97 (0.13)	1.93 (0.12)	1.94 (0.13)	4.37 (0.40)	3.95 (0.34)	3.98 (0.37)
France	1.62 (0.05)	1.62 (0.05)	1.62 (0.05)	3.96 (0.14)	3.91 (0.14)	3.90 (0.14)
Hungary	1.86 (0.09)	1.85 (0.09)	1.85 (0.09)	2.21 (0.06)	2.21 (0.06)	2.21 (0.06)
Italy	2.16 (0.18)	2.05 (0.15)	2.05 (0.16)	2.95 (0.23)	2.93 (0.22)	2.95 (0.22)
Japan	1.82 (0.14)	1.81 (0.13)	1.81 (0.13)	2.64 (0.25)	2.66 (0.23)	2.66 (0.23)
Philippines	1.94 (0.17)	1.89 (0.14)	1.90 (0.15)	2.74 (0.12)	2.74 (0.12)	2.74 (0.12)
Spain	2.23 (0.03)	2.23 (0.03)	2.23 (0.03)	3.32 (0.04)	3.31 (0.04)	3.31 (0.04)
United States	1.45 (0.06)	1.47 (0.06)	1.46 (0.06)	2.71 (0.13)	2.71 (0.13)	2.71 (0.13)
West Germany	1.96 (0.05)	1.95 (0.05)	1.95 (0.05)	2.10 (0.07)	2.11 (0.07)	2.11 (0.07)
West Malaysia	1.29 (0.12)	1.36 (0.11)	1.35 (0.12)	2.09 (0.10)	2.10 (0.10)	2.10 (0.10)
Yugoslavia	1.84 (0.31)	1.80 (0.21)	1.80 (0.23)	2.37 (0.31)	2.45 (0.28)	2.43 (0.30)
Denmark	1.61 (0.26)	1.67 (0.19)	1.67 (0.21)	3.26 (0.41)	3.14 (0.34)	3.13 (0.37)
Finland	1.86 (0.33)	1.80 (0.21)	1.81 (0.23)	2.62 (0.37)	2.67 (0.32)	2.67 (0.31)
Norway	1.34 (0.27)	1.52 (0.19)	1.52 (0.22)	2.09 (0.38)	2.27 (0.33)	2.26 (0.33)
Sweden	1.65 (0.25)	1.69 (0.19)	1.69 (0.19)	3.35 (0.63)	3.11 (0.45)	3.09 (0.49)

Note: Numbers in parentheses are estimated standard errors.

Table IV.3 Direct Estimator Versus Adjusted Estimator of the Altham Index in Simulation

Data Generating Model	Estimator	Total MSE	Average Correlation with $d(M_k, J)$	
			Pearson	Spearman's Rank
Quasi-perfect mobility	$\hat{d}^{\text{Direct}}(M_k, J)$	91.9	0.916	0.894
	$\hat{d}^{\text{Adjusted}}(M_k, J)$	73.5	0.919	0.886
Uniform inheritance	$\hat{d}^{\text{Direct}}(M_k, J)$	39.6	0.904	0.886
	$\hat{d}^{\text{Adjusted}}(M_k, J)$	22.3	0.940	0.918
Perfect blue-collar mobility	$\hat{d}^{\text{Direct}}(M_k, J)$	107.5	0.894	0.885
	$\hat{d}^{\text{Adjusted}}(M_k, J)$	74.0	0.904	0.873
Unidiff (full interaction)	$\hat{d}^{\text{Direct}}(M_k, J)$	77.0	0.867	0.855
	$\hat{d}^{\text{Adjusted}}(M_k, J)$	38.8	0.906	0.882

Table IV.4 Correlations of Direct and Adjusted Estimates of the Altham Index with $\hat{\phi}_k^{\text{Unidiff}}$.

Data Set	Estimator	Pearson's Correlation	Spearman's Rank Correlation
HG-16	$\hat{d}^{\text{Direct}}(M_k, J)$	0.858	0.832
	$\hat{d}^{\text{Adjusted}}(M_k, J)$	0.852	0.876
HG-15 (w/o Hungary)	$\hat{d}^{\text{Direct}}(M_k, J)$	0.917	0.846
	$\hat{d}^{\text{Adjusted}}(M_k, J)$	0.939	0.893
GLT-149	$\hat{d}^{\text{Direct}}(M_k, J)$	0.817	0.839
	$\hat{d}^{\text{Adjusted}}(M_k, J)$	0.803	0.899

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