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The Nonlinear Linkage Between Earnings Homogamy and Earnings Inequality Among Married Couples

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ABSTRACT More married couples today consist of two high-earning or two low-earning partners (i.e., earnings homogamy), which leads to greater earnings inequality in married-couple families. Surprisingly few studies have examined this relationship by earnings level, leaving open the question of whether the increase in earnings homogamy at each level of earnings contributes equally to between-couple earnings inequality. I address this question using data on urban China during 1988–2013. Changes in earnings homogamy account for 6% to 11% of the increase in between-couple inequality, but importantly, decomposition reveals that 57% to 68% of the overall impact is driven by the growing earnings homogamy among the top 20% of husbands and their wives. I reach the same finding by replicating the analyses using data from the United States. Two explanations account for this finding: (1) earnings homogamy has increased more among high earners; and (2) all else being equal, increases among high earners are mechanically more influential in shaping the level of between-couple inequality. These findings have important theoretical and policy implications.

KEYWORDS Earnings inequality • Earnings homogamy • Urban China • CHIP

Introduction

In many countries, husbands' and wives' incomes are becoming similar—more economically homogamous (Esping-Andersen 2007). The rise of economic homogamy has its roots in a wide range of demographic transformations, including marital delay, fertility decline, and improvement in women's education and labor force participation (Lichter and Qian 2019). It has important implications for social inequality by reshaping the composition of a population: given that more couples today consist of two high-income or two low-income partners, inequality between married-couple families will intensify. Further, the rising concentration of economic resources among high-powered, dual-career couples enhances the family-based advantage for their children, which propagates the inequality of opportunity across generations (Rauscher 2020; Reardon 2018).

Although this income homogamy-inequality relationship has drawn significant attention (for a review of the literature, see Schwartz 2013), surprisingly few studies have

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examined this relationship by income level. This lack of research leaves open the question of whether the increase in income homogamy at each level of income contributes equally to between-couple inequality.

This question is important for two reasons. First, the socioeconomic processes at different quantiles of the income distribution differ (Liao 2006, 2016; Reardon and Bischoff 2011). A quantile-based approach takes into account this socioeconomic heterogeneity and facilitates more targeted policy responses. If increases in income homogamy among high earners contributed more to inequality than increases in homogamy among low earners, future policy may prioritize efforts that mitigate the disequalizing impact of the increases in income homogamy among high earners, such as adjusting the degree of joint taxation of top-earning married couples. But if the opposite were true, policy could consider tax reforms that encourage nonworking partners in low-income couples to join the workforce (Bick and Fuchs-Schündeln 2018).

Second, and more importantly, unlike the traditional dimensions along which homogamy patterns are examined (e.g., by education, race, occupation, and age), economic resources, such as income, always follow a highly right-skewed distribution. For example, in 2014, Americans in the top 1% of the income distribution earned 81 times more than those in the bottom 50% (Piketty et al. 2016). As I show later, this feature of income distribution suggests that even if income homogamy increases equally at each income level, *ceteris paribus*, the increase among high earners produces a much larger amount of inequality between couples than a similar increase among middle or low earners. Past research has paid little attention to this potential mechanism.

This article examines the income homogamy-inequality association by income level. I start by analyzing the empirical case in urban China. Urban China provides a unique opportunity to study the nonlinear change in the pattern of income homogamy and its nonlinear impact on between-couple inequality. To implement the aforementioned quantile-based idea, I combine a reweighting method (DiNardo et al. 1996) with the iGini measure proposed by Liao (2019), which decomposes the Gini index into an additive sum of each individual unit's contribution to the overall inequality. I extend this approach to the squared coefficient of variation (CV^2) by rewriting CV^2 into a Gini-type index (Chameni Nembua 2006) and integrate the Gini index and CV^2 into a unified, additive decomposition framework. This framework shows how different configurations of the Gini index and CV^2 can produce different decomposition results.

My estimated overall impact of the growing labor income homogamy on the increase in between-couple inequality during 1988–2013 in urban China ranges from 6% to 11%, depending on the measures used. However, 57% to 68% of the estimate is driven by the increase in labor income homogamy among the top 20% of husbands and their wives. I find the similar pattern by replicating the analyses using data from the United States (1970–2013).

Why is the impact of income homogamy among high earners overwhelmingly large in both urban China and the United States? I offer two explanations. First, income homogamy has increased more among high earners in both contexts. Second, all else being equal, increases in homogamy among high earners mechanically generate more between-couple inequality than among lower earners. This mechanical explanation asserts a deterministic mechanism. Many demographic effects are produced mechanically (Bhrolcháin and Dyson 2007). For example, Lam and Marteleto (2008) showed that although the fertility transition reduced family size and children enjoyed less competition for resources within families, children would still face increasing competition at the population level for an extended period because population momentum would mechanically keep the sizes of successive birth cohorts increasing. My simulations find that the impact of increases in income homogamy among high earners is always disproportionately large, *ceteris paribus*. Further, this mechanical pattern is found to be caused by the fact that income distributions among married men and women are right-skewed and unequal. If incomes could be more equally distributed among men and women, the impact of increases in income homogamy among high earners would be less dominant.

Taken together, my findings suggest that the overall impact of the changing income homogamy on trends in between-couple income inequality, as is often the focus in the previous literature, is heavily shaped by the change in income homogamy among a small group of couples near the top of the income distribution. These findings challenge commonly held assumptions and call for more research on the formal relationship between economic homogamy and family economic inequality.

Recent Empirical Research

Recent discussion about economic inequality centers on the rising income concentration at the top of the distribution, a phenomenon found in Anglo-Saxon countries, India, and China (Piketty 2014). Current explanations include (but are not limited to) the rising demand for skilled workers induced by technological advances, institutional shifts that created new “rents” for top earners, and ideological changes that legitimize supersalaries (Autor et al. 2008; Piketty 2014; Weeden and Grusky 2014). Further, although capital gains make up a significant portion of income for those at the top of the income distribution, labor incomes or earnings also increasingly concentrate at the top (Piketty 2014). It is within this context that the dynamics of *earnings* homogamy attract growing attention as a potential demographic factor behind the surge in family income inequality. This explanation differs from the aforementioned economic and sociopolitical explanations by emphasizing the impact of compositional shifts in a population due to changes in family behavior.

Conventionally, earnings homogamy is measured by a single summary measure, such as the Pearson’s coefficient of correlation (Cancian and Reed 1999). The impact of earnings homogamy on the earnings inequality between married couples is usually assumed to be positive and linear: holding other factors constant, when the correlation between spouses’ earnings increases, earnings inequality between couples also increases. Recent studies, however, challenge this linear imagination by paying more attention to the *pattern* of earnings homogamy (Ciscato and Weber 2020; Reed and Cancian 2012). Using U.S. data, Schwartz (2010) was among the first to show that a switch in focus from the level to the pattern of earnings homogamy is indeed significant. She found that the changing earnings homogamy among dual-earner couples had increased inequality mainly in the upper part of the distribution, whereas the changing relationship between husbands’ earnings and wives’ employment exacerbated inequality mainly in the lower part of the distribution.

Another discussion concerns the importance of changes in assortative mating in explaining the observed increase in earnings homogamy and its impact on inequality. Gonalons-Pons and Schwartz (2017) found little change in assortative mating by earnings or earnings potential across marriage cohorts in the United States, concluding that changes in assortative mating explain little of the rising correlation between spouses' earnings or its impact on between-couple inequality.

Limitations of Prior Research

Recent studies have contributed greatly to an understanding of the relationship between income homogamy and between-couple inequality. However, two essential questions remain underexplored. First, how does the degree of income homogamy change at each level of income? Recent studies have noted the rise of high-earning, dual-career couples in many countries (Costa and Kahn 2000; Dribe and Stanfors 2010), but they have not quantified its impact on family income inequality. Given that the recent upturn in inequality features a top-heavy form, it is critical to know whether this trend is at least partly driven by the rise of "power couples," in which both partners are high earners.

Second, do changes in income homogamy make equal contributions to between-couple inequality regardless of where in the distribution the changes occur? This question concerns the linearity (or more accurately, homogeneity) of the impact of income homogamy on between-couple income inequality. In a simulation analysis, Sudo (2017) found that rising income homogamy among men in the top 20% generates more inequality between households (as measured by the Gini index) than rising income homogamy among middle- or low-income men. However, it is unclear why it is the case and whether the finding holds across inequality measures or social contexts.

Past research has examined social contexts to understand the potentially nonlinear impact of socioeconomic homogamy on between-couple inequality. For instance, Breen and Salazar (2011) and Breen and Andersen (2012) discussed the impact of the changes in educational homogamy on family income inequality by level of education in the United States and Denmark. They concluded that whether the contextual prevalence of women's employment allows educational homogamy to be translated into income homogamy plays a key role in determining the impact of educational homogamy on family income inequality. Their explanation implies that income homogamy is a key mediator between educational homogamy and family income inequality. However, it remains unclear how income homogamy at different levels of income affects family income inequality differently. Nor is it clear whether this income homogamy-inequality association is as context-dependent as the educational homogamy-inequality association.

Why Is Urban China an Interesting Case?

In most western countries, female labor supply has increased over time. Better-skilled women take advantage of new job opportunities and tend to have higher-earning husbands (Esping-Andersen 2009). Therefore, the secular increase in female labor supply is accompanied by increases in earnings homogamy. How would earnings homogamy change over time if female labor supply declined? Would a secular decline in female labor supply be accompanied by a decline in the association between spouses' earnings?

I use data from urban China to examine the aforementioned questions. In the late 1980s, about one-quarter to one-half of state-owned enterprises in urban China lost money, partly because these enterprises hired more workers than needed as a result of the "full-employment" policy under the old socialist regime (Ding et al. 2009). A market-oriented reform in 1992 allowed enterprises to lay off employees, and female labor force participation plunged thereafter (Wu 2019). In my analytic sample (described later), the share of married women aged 30–49 having positive annual earnings dropped from 98% in 1988 to 86% in 2013. In this context, urban China offers a unique opportunity to longitudinally observe how the association between spouses' earnings would evolve when the overall labor market prospects for women deteriorate over time.

Data

I use repeated cross-sectional data from the China Household Income Project (CHIP), which was housed at the China Institute for Income Distribution at Beijing Normal University (Li et al. 2013). CHIP collects separate samples from rural and urban households. This study uses the urban samples from the first and last survey years (i.e., 1988 and 2013). Data from years in between (i.e., 1995 and 2002) are used in descriptive statistics. The 1988 urban sample covers only households headed by urban *hukou* holders. In 2013, CHIP collected an additional sample of urban households headed by rural *hukou* holders (the "rural migrant sample"), which is included in my 2013 sample. Weights are used in all analyses (Song et al. 2013).

My analytic sample consists of urban married couples in which both spouses are aged 30–49 and live together. The sample excludes couples in which at least one spouse does not work because of disability, retirement, or schooling, as well as couples in which at least one spouse has contradictory or missing information on earnings or has negative earnings. The numbers of couples excluded for these reasons are 26 in 1988 (0.82%) and 40 in 2013 (1.27%). Couples in which the husband has zero annual earnings are also omitted (Hryshko et al. 2017): 2 in 1988 and 38 in 2013. As a result, the number of couples with zero-earning husbands is too small to be compatible with my methodological approach (see the next section for details). Finally, the CHIP data are not top-coded. Because the inequality measure, CV^2, is sensitive to outliers in the distribution, I recode the top 1% (within gender and survey year) of husbands' and wives' earnings to equal the earnings at the 99th percentile. Results are similar if the top-coded couples are dropped from my sample.

The urban population in China increased from 26% of the total population in 1988 to 56% in 2013 (Fong et al. 2019). This rapid increase was partly driven by the massive influx of rural migrants. CHIP data may still underrepresent the rural migrant population in urban China (Li et al. 2013). This is arguably less of a problem for the 1988 sample because the migration rate then was relatively low (Ma et al. 1997). In the 2013 sample, the share of rural migrant couples (i.e., rural *hukou* couples living in urban households) is 13.4% before weighting and 23.5% after weighting. Nevertheless, weighting would not solve the problem if the sample systematically underrepresented short-term migrants. To evaluate the robustness of my results, I construct an alternative sample from the 2014 wave of the China Labor-force Dynamics Survey (CLDS 2014), a nationally representative household survey of the labor force population. This survey adopts a different sampling design that is more consistent with international standards (Hao and Liang 2016). My final analytic sample from the CHIP data consists of 4,613 urban couples in 1988; 2,966 in 1995; 2,650 in 2002; and 2,277 in 2013. CLDS 2014 yields a much smaller sample ($N=988$) and will be mainly used in descriptive statistics. More details on data and robustness checks are provided in the online appendix.

Measures

In this study, I focus on annual earnings. *Annual earnings* are defined as the sum of wages (including salaries, nonwage compensation, and nonmonetary benefits) and self-employment incomes, minus income tax (Ding et al. 2009). Earnings are further adjusted for differences in the cost of living among provinces according to Brandt and Holz (2006). Earnings inequality is measured by the Gini index and the squared coefficient of variation, CV^2. Although CV^2 is less popular than Gini, it is widely used for research on this topic (for a summary of the literature, see Nieuwenhuis et al. 2017).

The joint distribution of husbands' and wives' earnings consists of the gender-specific marginal earnings distributions and the association between spouses' earnings. Past studies have primarily focused on the former, particularly in research on the impact of the change in the marginal distribution of wives' earnings on between-couple inequality (for an empirical examination of this topic in the context of urban China, see Ding et al. 2009; for a theoretical discussion, see Sudo 2017). Here, I follow Schwartz (2010) and focus on the latter: the association between spouses' earnings.

I measure the association between spouses' earnings by *gender-specific* earnings rank (Bredemeier and Juessen 2013; Schwartz 2010). Husbands' earnings are classified into deciles.[1] Wives' earnings are classified into 11 categories: 1 zero-earnings category along with the 10 decile categories. Cross-tabulating husbands' and wives' earnings categories results in a 10×11 contingency table for each year. The shifts in the pattern of earnings homogamy are operationalized into the shifts in the relative frequencies of the 110 couple types over time. This measure relies on earnings ranks and is unaffected by the changes in the marginal earnings distributions among husbands and wives with positive earnings (e.g., changes in the absolute distances between earnings ranks, increases in the overall level of earnings over time).

However, the current measure is still not completely free of changes in the marginal distributions because it can still be affected by the changing share of wives with zero earnings. I use iterative proportional fitting to remove this component (Deming and Stephan 1940). Therefore, my measure of the pattern of changes in earnings homog-

[1] Husbands' earnings are classified into 10 instead of 11 categories because there are too few zero-earning husbands to be included in that category. Including them in the cross-tabulation would produce an 11×11 table that contains a few cells with very few or zero observations; the reweighting function $\tilde{\psi}$ (see Eq. (3)) for certain couple types would then be extremely susceptible to sampling errors and would be either very large or very small. Because of the small number of such couples, I do not expect that the exclusion of them would change my results (see the online appendix for sensitivity checks).

amy is entirely free of changes in marginal distributions and is conceptually identical to the measurement used in Schwartz (2010). As I explain later, focusing on the pattern of earnings homogamy completely independent of the marginal earnings distributions allows me to demonstrate how the impact of the former on between-couple inequality is mechanically moderated by the latter.

Methods

The Gini index and CV^2 can be expressed in a unified form as follows (Chameni Nembua 2006):

$$G(\alpha) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right|^{\alpha}}{2n^2\bar{x}^{\alpha}} \; (\alpha \geq 1), \tag{1}$$

where x_i and x_j are the earnings of ith and jth individual unit in the sample/population of size n. $\bar{x}$ is the sample/population mean earnings. $G(\alpha)$ is the Gini index when $\alpha = 1$ and CV^2 when $\alpha = 2$. It contains three components. The first component, $\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|^{\alpha}}{n^2}$, measures the average of the absolute differences in earnings between all possible pairs of individual units. The first component is then scaled by the second, $\frac{1}{2\bar{x}^{\alpha}}$, to ensure translation invariance—a desirable property of relative inequality measures. The third component, which already appears in the first two components, is the inequality-aversion parameter α. A larger value of α makes the earnings advantage of high earners less tolerable to the inequality index. It represents the researcher's moral preference about the nature of inequality. Clearly, the first component is the cornerstone of this type of inequality measure. When $\alpha = 1$, the first component is the Gini mean difference (GMD) (Dagum 1997). When $\alpha = 2$, it is simply variance. Both GMD and variance are measures of variability. After being scaled and parameterized by the second and the third components, GMD and variance become measures of inequality.

Liao (2019) showed that the Gini index is an additive sum of its individual components, *iGini*. Here, the generalized Gini-type index $G(\alpha)$ can be rewritten as the sum of each individual unit's contribution, $iGini(\alpha)_i$, so that $iGini(\alpha)_1 + iGini(\alpha)_2 + \cdots + iGini(\alpha)_n = G(\alpha)$:

$$iGini(\alpha)_i = \frac{\sum_{j=1}^{n}\left|x_i - x_j\right|^{\alpha}}{2n^2\bar{x}^{\alpha}}. \tag{2}$$

$iGini(\alpha)_i$ is a scaled sum of the pairwise earnings differences between unit i and all other units in the population. It quantifies the contribution of each unit i to the overall level of inequality. The $iGini(\alpha)_i$s of all units in a sample/population amount to $G(\alpha)$, the overall inequality of the sample/population.

Change in earnings homogamy affects inequality by altering the relative group size of each couple type k ($k = 1, 2, \ldots, 110$), which is essentially a reweighting effect. To quantify this effect, I follow the demographic tradition of standardization: I standardize the distribution of couple types in 2013 back to that at the beginning of the period (i.e., 1988) (Kitagawa 1955; Liao 1989). The standardized overall inequality in 2013 represents what the level of between-couple inequality in 2013 would be *had there been no change in the pattern of earnings homogamy since 1988*. The reweighting function $\tilde{\psi}$ used in standardization is defined as (DiNardo et al. 1996; Fan and Qian 2019):[2]

$$\tilde{\psi} = \frac{\tilde{P}(k\,|\,t=1988)}{P(k\,|\,t=2013)}. \tag{3}$$

The denominator is the proportion of couples of type k ($k=1, 2, \ldots, 110$) as observed in 2013. The numerator is the margin-adjusted proportion of couples of type k in 1988—that is, the proportion of couple type k in 1988 if the marginal distributions of husbands' and wives' earnings categories mimicked those in 2013. Margins are adjusted through iterative proportional fitting (Deming and Stephan 1940). The difference in the observed and standardized levels of inequality in 2013, $G(\alpha)^{observed} - G(\alpha)^{standardized}$, quantifies the overall impact of standardization on between-couple inequality in 2013. The overall impact can be rewritten as a sum of the differences between observed and standardized individual components of the overall inequality in 2013:

$$G(\alpha)^{observed} - G(\alpha)^{standardized} = \sum_{i}^{n}[iGini(\alpha)_i^{observed} - iGini(\alpha)_i^{standardized}]. \tag{4}$$

Equation (4) makes it clear how standardization has reweighted each individual couple's contribution to the overall level of between-couple inequality in 2013. In subsequent analyses, I group these individual components of inequality by husbands' earnings decile because the pattern of earnings homogamy is measured at the decile level. Sampling weights and the reweighting function $\tilde{\psi}$ are incorporated into Eqs. (1) and (2) according to Liao (2016).

Descriptive Statistics

Trends In Between-Couple Earnings Inequality

Figure 1 shows trends in between-couple earnings inequality in urban China. The Gini index and CV^2 of between-couple earnings inequality increased from 1988 to 2002 before it leveled off in 2002–2013 (panel a). Panel b shows trends in inequality measured by the 90/50 and 10/50 percentile ratios. Both measures produce trends similar to those summarized by Gini and CV^2. Although these trends are based on the sample of married couples, they are similar to the findings obtained from broader samples (Piketty et al. 2019).

Trends in Earnings Homogamy

Figure 2 displays the trends in the overall *level* of earnings homogamy. The Pearson's coefficient of correlation of spouses' earnings fluctuates within a narrow range around

[2] I am grateful to Wen Fan for the code.

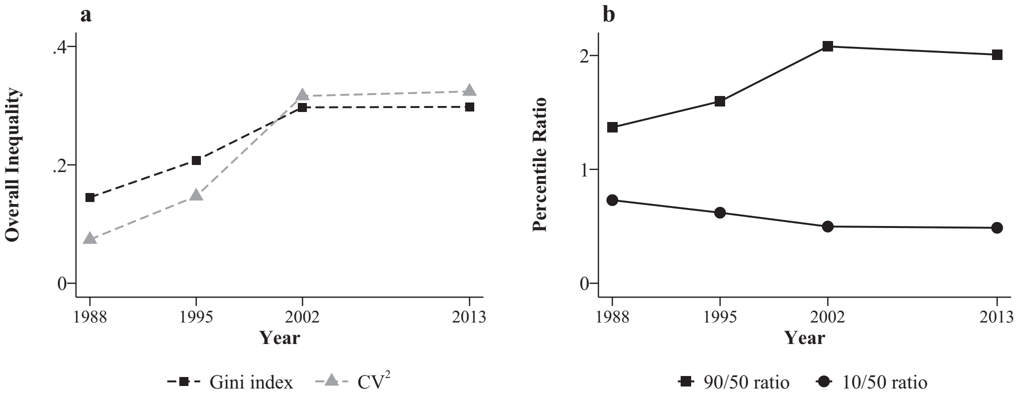

Fig. 1 Trends in earnings inequality between married couples in urban China: 1988–2013. *Source:* CHIP 1988, 1995, 2002, and 2013.

.4 (panel a). Because I focus exclusively on the changing association between spouses' earnings net of changes in marginal distributions, I fit the log-multiplicative layer effect model (Xie 1992) to the 10×11 contingency tables to isolate the former from the latter. As in panel b, the multiplicative association coefficient is 1.34 in 2013, compared with the fixed value of 1 in 1988, showing an increase of 34% in the overall level of the association between spouses' earnings. Clearly, the effects of changes in marginal distributions and changes in the net association between spouses' earnings offset each other, resulting in flat trends in the Pearson's coefficient of correlation of spouses' earnings.

Figure 3 illustrates the changes in the *pattern* of earnings homogamy defined as the net association between spouses' earnings categories. Panel a of Figure 3 shows the pattern of homogamy in 1988. The number in each cell refers to the status inheritance ratio, or sorting parameter, which is the ratio of the observed cell frequency of a joint combination of husbands' and wives' earnings categories to the expected cell frequency assuming mutual independence between husbands' and wives' earnings categories (Eika et al. 2018; Goodman 2007). For instance, the ratio in the lower-right corner of panel a is 3.5, meaning that the observed number of couples in which both spouses' earnings are in the top decile (within their own gender) is 3.5 times the number of couples expected under independence of husbands' and wives' earnings categories. Note that these sorting parameters do not measure spouses' earnings association among couples within cells.

Panel b of Figure 3 shows changes in these sorting parameters from 1988 to 2013 by subtracting the 1988 parameters from the parameters in 2013. Compared with 1988, zero-earning wives in 2013 became less likely to have a husband with either very low (i.e., bottom-decile) or very high (i.e., top-decile) earnings. Among dual-earner couples, husbands in the middle eight deciles (the 6th–9th deciles in particular) became more likely to have a wife whose earnings rank is one to three deciles above his rank. Panel c replicates the calculations in panel b using data from CLDS 2014. The size of this alternative sample is much smaller, so the distribution of the sorting parameters is less smooth. Nevertheless, the overall pattern is similar: the sorting parameters decreased near the bottom of the distribution and increased near the top of the distribution. The increases in the sorting parameters elsewhere are largest in cells slightly below the main diagonal.

Recall that these earnings categories are gender-specific. Because of gender pay gaps, couples in which the wife's earnings decile is slightly higher than the husband's are

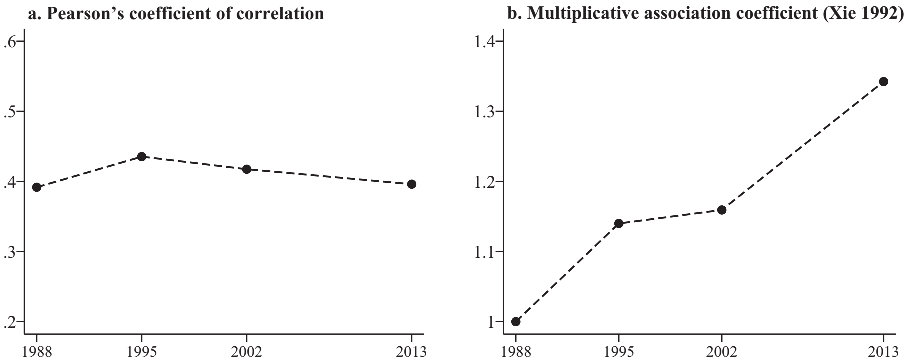

Fig. 2 Trends in the overall level of earnings homogamy in urban China: 1988–2013. *Source:* CHIP 1988, 1995, 2002, 2013.

actually equal earners. Panel d of Figure 3 shows changes in sorting parameters when husbands' and wives' earnings are classified regardless of gender. The general pattern still holds, although now the sorting parameters in the cells on or slightly above the main diagonal exhibit the largest increases. This finding agrees with Schwartz's (2010) finding in the United States that the absolute difference between spouses' earnings is useful in understanding the pattern of earnings homogamy measured in relative terms (i.e., using gender-specific earnings ranks). Like Schwartz (2010), I adopt the relative measurement (i.e., panel b) in subsequent analyses because my interest is between-couple inequality. Earnings homogamy is more consequential to between-couple inequality when, for instance, female top-earners are married to male top-earners rather than male equal-earners. Results are similar if earnings categories are defined regardless of gender (i.e., panel d).

Interpreting the Trends in Earnings Homogamy in Urban China

Why has earnings homogamy strengthened among high earners and yet weakened among low earners? A systematic examination of the causes behind these diverging trends is beyond the scope of this article. Here I discuss one potential cause: the surge in internal migration. China's market-oriented reform accelerated the growth of its manufacturing sector, which attracted many rural Chinese residents to work in urban areas. The internal migration boom reshaped the urban marriage market (Wang and Schwartz 2018). Although migrants are, on average, less educated, migrants with higher education have a greater chance of being integrated into the urban marriage market (Qian and Qian 2017). High-earning, urban-born residents might be more likely to marry a high earner than before if the urban marriage market has expanded to include rural migrants with high education. This may strengthen earnings homogamy near the top of the distribution.

Because China's market reform aimed at improving economic productivity, employment of married women of low-income husbands suffered most in the early stages of the reform because of their low skills. Since China joined the World Trade Organization in the early 2000s, the employment rate of women with low-income husbands has declined more slowly than that of women with higher-income husbands and even

a. Observed pattern in 1988

WE \ HE	1	2	3	4	5	6	7	8	9	10
0	2.0	0.7	0.8	0.6	0.5	0.6	0.7	1.0	0.6	2.5
1	3.1	1.4	1.0	0.8	0.6	0.7	0.7	0.6	0.5	0.6
2	2.6	1.9	1.3	0.9	0.6	0.8	0.6	0.5	0.4	0.4
3	1.3	1.9	1.4	1.0	0.9	1.2	0.7	0.7	0.4	0.5
4	0.7	1.5	1.5	1.2	1.3	1.0	0.8	0.8	0.6	0.5
5	0.6	1.2	1.4	1.3	1.3	1.2	1.0	0.9	0.6	0.6
6	0.3	0.7	1.2	1.5	1.4	1.2	1.3	0.8	1.0	0.7
7	0.4	0.4	0.9	1.3	1.5	1.1	1.3	1.6	0.9	0.8
8	0.2	0.5	0.5	0.9	1.2	1.3	1.5	1.5	1.6	1.0
9	0.4	0.3	0.5	0.8	0.8	1.0	1.4	1.5	2.1	1.3
10	0.2	0.4	0.4	0.5	0.6	0.6	0.9	1.1	1.9	3.5

b. Changes from 1988 to 2013

WE \ HE	1	2	3	4	5	6	7	8	9	10
0	–1.0	0.4	0.0	0.3	0.4	0.7	0.1	–0.1	0.4	–1.2
1	0.7	–0.5	–0.1	0.1	0.2	–0.1	0.1	–0.2	–0.1	–0.1
2	0.0	–0.4	0.1	0.2	0.4	–0.1	0.0	0.0	–0.1	–0.1
3	0.1	0.3	–0.1	0.1	0.2	–0.5	0.0	0.0	0.1	–0.2
4	–0.5	1.3	–0.1	–0.3	–0.4	0.1	–0.1	0.0	0.0	0.0
5	0.1	0.2	0.4	0.4	0.1	–0.7	–0.2	–0.2	–0.1	–0.1
6	0.1	–0.3	0.1	0.6	–0.1	–0.4	–0.1	0.2	0.2	–0.1
7	–0.2	0.1	0.1	0.2	0.7	0.2	0.2	–1.0	–0.3	0.0
8	0.0	–0.3	–0.1	–0.4	–0.1	1.5	–0.3	–0.1	–0.4	0.3
9	–0.3	–0.1	0.0	–0.2	–0.3	–0.5	1.0	1.0	–0.5	–0.1
10	0.1	–0.3	–0.2	–0.4	–0.5	–0.2	–0.1	0.4	1.1	0.1

c. Changes from 1988 to 2013 (CLDS sample)

WE \ HE	1	2	3	4	5	6	7	8	9	10
0	–0.9	0.1	0.1	0.1	0.9	0.3	0.5	–0.1	0.4	–1.3
1	–0.3	0.3	0.1	0.0	0.8	0.0	–0.5	–0.4	–0.1	–0.1
2	–0.9	1.4	–0.4	–0.1	0.5	–0.6	–0.2	0.1	0.2	–0.1
3	0.0	–0.5	0.0	0.1	0.8	–0.6	0.4	0.0	–0.2	–0.1
4	–0.5	0.5	–0.5	0.8	–0.8	0.3	0.3	0.2	–0.1	–0.2
5	0.1	–0.1	1.3	–0.1	–0.8	–0.3	0.1	–0.4	0.5	–0.4
6	0.8	–0.5	0.5	0.9	–0.4	0.0	–0.7	–0.1	–0.3	–0.3
7	–0.1	0.5	–0.4	0.4	0.1	0.6	–0.1	–0.1	–0.6	–0.1
8	0.3	–0.1	–0.4	–0.8	–0.4	1.1	0.8	0.1	–0.5	–0.2
9	–0.1	–0.2	–0.2	–0.3	–0.5	0.0	–0.2	1.4	0.0	0.1
10	0.3	–0.4	0.2	0.1	–0.5	–0.1	–0.3	–0.7	0.7	0.8

d. Changes from 1988 to 2013 (absolute)

WE \ HE	1	2	3	4	5	6	7	8	9	10
0	–0.6	0.1	0.0	–0.2	0.5	0.4	0.2	0.2	–0.2	–0.6
1	–1.0	–0.3	0.0	0.2	–0.1	0.4	0.2	0.3	–0.2	0.0
2	0.2	0.0	0.7	0.1	–0.1	0.3	–0.2	0.1	0.0	–0.3
3	–0.2	–0.1	0.1	0.5	0.1	0.1	–0.1	–0.3	0.2	–0.2
4	0.2	–0.1	–0.3	0.1	0.6	–0.4	–0.1	0.1	–0.1	0.1
5	–0.3	0.2	0.0	–0.4	–0.2	0.0	0.3	–0.2	0.0	0.1
6	0.3	–0.1	–0.6	–0.4	–0.3	0.6	0.3	–0.1	–0.1	0.0
7	–0.1	–0.2	–0.3	–0.5	0.0	–0.5	0.6	0.2	0.1	–0.1
8	0.0	–0.2	–0.3	–0.2	0.0	–0.6	–0.5	0.2	0.6	0.3
9	–0.3	–0.3	0.0	–0.3	–0.5	–0.4	0.3	0.2	0.4	0.2
10	0.3	0.0	–0.3	0.0	–0.2	–0.5	–0.2	–0.4	0.2	0.9

0 1 2 3 4 -2 -1 0 1 2

Fig. 3 Changes in the pattern of earnings homogamy in urban China: 1988–2013. HE=husband's earnings category. WE=wife's earnings category. Cell numbers refer to (change in) sorting parameters as defined in the main text.

rebounded in more recent years (Wu and Zhou 2015). China's transition to an export-oriented economy may have cushioned the employment plunge among low-skilled women: China's light manufacturing (such as apparel and footwear) attracts a large number of low-skilled rural women to work in urban areas (Chen et al. 2013). Rural migrants were disadvantaged in the urban marriage market, yet some managed to marry urban-born residents with the potential cost of marrying a comparatively less-educated urban partner (Zeng and Liao forthcoming). To the extent that such a status exchange between migrant status and educational status reflects an exchange between migrant and (gender-specific) economic status, this may depress earnings homogamy near the bottom of the distribution by increasing the number of couples in which the husband and the wife differ in economic standing.

Finally, recent changes in selection into marriage in urban China could also have affected trends in earnings homogamy (Yu and Xie 2020). I discuss this issue further in the online appendix.

Urban China Versus the United States

Figure 4 compares the pattern of earnings homogamy in 2013 between urban China (panel a) and the United States (panel b). The U.S. data come from the Current Population Survey (CPS) (Flood et al. 2020). The sample and earnings measures are

a. Urban China, 2013

WE \ HE	1	2	3	4	5	6	7	8	9	10
0	10.3	10.2	8.5	8.7	8.4	13.2	8.1	8.8	10.8	13.1
1	37.8	8.9	9.3	9.3	7.6	5.9	7.6	4.8	4.3	4.7
2	25.7	14.8	14.1	10.7	10.2	7.1	6.0	5.0	3.4	3.0
3	14.5	22.0	13.4	10.8	10.8	7.3	6.2	6.5	5.4	3.1
4	2.7	27.0	14.4	9.5	8.7	11.3	7.7	7.9	6.2	4.5
5	7.6	14.6	18.1	16.2	13.4	5.1	7.7	7.0	5.3	4.9
6	3.9	3.4	13.0	20.3	12.5	7.9	11.7	10.0	11.0	6.3
7	1.7	4.5	9.6	14.4	21.9	12.4	14.3	6.2	6.7	8.5
8	2.0	2.0	3.8	4.4	11.5	27.6	11.2	14.2	11.3	12.1
9	0.6	1.3	4.9	5.6	5.2	5.5	23.8	25.4	15.8	11.9
10	3.3	1.1	2.3	1.0	1.1	4.4	7.3	14.6	29.5	35.5

b. United States, 2013

WE \ HE	1	2	3	4	5	6	7	8	9	10
0	11.4	11.5	10.0	8.5	7.6	8.4	8.9	9.1	10.9	13.7
1	13.4	8.6	9.0	8.7	10.0	8.2	9.3	9.9	11.0	11.9
2	16.9	12.8	10.8	9.6	9.7	8.8	9.5	9.0	7.1	6.0
3	13.2	14.4	11.3	11.7	9.1	10.5	9.4	8.5	6.2	5.9
4	9.8	15.1	12.2	14.0	11.3	9.8	8.9	8.7	5.9	4.3
5	8.3	10.8	15.5	13.0	13.0	10.8	9.3	8.6	6.4	4.4
6	6.0	6.4	13.5	16.7	10.8	12.4	9.0	10.5	8.3	6.5
7	7.7	6.5	10.9	12.1	16.2	13.3	9.4	10.0	8.3	5.7
8	4.4	6.8	6.4	10.0	13.7	13.6	13.6	11.9	10.7	8.8
9	5.6	6.0	5.8	7.1	10.5	13.3	14.8	13.7	13.5	9.8
10	5.9	4.4	4.6	5.5	7.2	8.2	11.5	13.7	17.6	21.5

c. Urban China, change from 1988 to 2013

WE \ HE	1	2	3	4	5	6	7	8	9	10
0	–9.7	3.7	0.2	3.0	3.7	7.0	1.4	–1.3	4.3	–12.2
1	6.6	–5.1	–0.5	1.0	1.6	–0.8	0.9	–1.6	–0.8	–1.2
2	0.2	–3.7	0.7	1.6	4.1	–0.6	–0.4	0.0	–1.1	–0.9
3	1.5	2.8	–1.0	0.5	2.2	–5.1	–0.4	–0.1	1.2	–1.5
4	–4.6	12.6	–0.5	–2.9	–4.2	1.1	–0.8	–0.4	0.1	–0.3
5	1.4	2.4	4.1	3.7	0.8	–6.7	–2.4	–1.8	–1.0	–0.6
6	0.6	–3.3	1.0	5.8	–1.3	–3.7	–1.2	1.7	1.4	–0.9
7	–1.9	0.7	0.9	1.8	7.4	1.5	1.5	–9.5	–2.7	0.3
8	0.0	–2.8	–0.8	–4.5	–0.8	14.6	–3.4	–0.8	–4.3	2.6
9	–3.4	–1.5	0.3	–1.9	–2.7	–4.6	10.0	10.2	–5.3	–1.1
10	1.1	–3.2	–1.5	–3.8	–4.7	–1.8	–1.2	4.1	10.7	0.4

d. United States, change from 1970 to 2013

WE \ HE	1	2	3	4	5	6	7	8	9	10
0	3.1	3.1	1.5	–0.1	–1.2	–1.0	–1.4	–2.1	–1.0	–0.9
1	–0.1	–0.4	2.3	–0.3	–0.1	–3.1	–0.8	–0.4	–1.8	4.7
2	5.2	1.3	2.7	–0.2	–1.5	–1.7	–0.1	–1.2	–4.4	0.0
3	1.8	2.8	–0.4	0.3	–1.6	–0.2	0.7	–0.7	–0.8	–1.8
4	–5.0	2.0	0.1	2.6	1.6	–0.4	–0.1	3.1	–2.0	–1.9
5	–8.8	–0.1	3.3	0.6	2.0	3.3	–1.6	0.6	–0.6	1.2
6	–8.7	–5.9	1.5	4.0	–1.2	2.5	1.5	1.4	1.8	3.2
7	–5.5	–10.2	–1.8	0.6	4.0	4.0	1.3	2.2	3.0	2.5
8	–4.3	–7.8	–8.1	–0.9	3.1	1.5	3.0	4.4	3.8	5.3
9	–2.2	–4.1	–9.2	–5.7	–1.8	1.7	5.0	6.1	5.7	4.5
10	–2.3	–2.4	–4.1	–6.8	–3.6	–1.6	–0.6	1.3	6.4	13.7

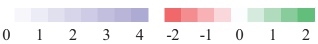

Fig. 4 Comparison of the changing pattern of earnings homogamy between urban China and the United States. HE=Husband's earnings category. WE=Wife's earnings category. Cell numbers refer to (change in) sorting parameters as defined in the main text. Periods start from 1970 for the United States to be comparable to Gonalons-Pons and Schwartz (2017).

similar (Eika et al. 2018). The number in each cell represents the percentage distribution of husbands' earnings deciles conditional on wives' earnings category, so all numbers in each row sum to 100%. These conditional probabilities are margin-free because husbands' earnings deciles are equal-sized. This feature allows us to interpret the pattern of the net association between spouses' earnings from the wife's perspective. Despite different socioeconomic contexts, the cross-sectional pattern of earnings homogamy in urban China and the United States in 2013 are similar. Zero-earning wives were more likely to have a husband with either very low or very high earnings. Among dual-earner couples, earnings homogamy seemed stronger in urban China than in the United States, especially at the tails of the distribution. In urban China, 36% of the top-decile wives had husbands whose earnings were also in the top decile, compared with 22% in the United States.

Panels c and d of Figure 4 compare the changes in the pattern of earnings homogamy between the two contexts. First, although earnings homogamy among high earners increased in both countries, the increase was larger in the United States. Second, over time, zero-earning wives became less likely to have a husband from the bottom decile in urban China, but they became more likely to have a bottom-decile husband in the United States. As a result, unlike in urban China, earnings homogamy in the United States has increased across the whole earnings distribution. Furthermore, the increases in the sorting parameters tend to be concentrated in cells slightly below the main diagonal in both urban China and the United States (except in the top decile), reflecting the importance of the absolute differences between spouses' earnings (Schwartz 2010).

Decomposition of the Trends in Earnings Inequality

This section quantifies the contribution of changes in earnings homogamy to the observed increase in between-couple earnings inequality. Table 1 shows the decomposition of the Gini index step by step. In panel a, the observed Gini indices in 1988 and 2013 are provided in columns A1 and A2. Column B provides the standardized level of inequality in 2013. Column C reports that the observed Gini index rose by .1651 Gini index points from 1988 to 2013. Column D reports that the Gini index would rise by only .1549 if the pattern of earnings homogamy remained unchanged since 1988. Therefore, 6.2% (.01 Gini index point) of the observed increase in between-couple earnings inequality can be attributed to the changing pattern of earnings homogamy (column E in panel a), which is similar to the redistributive effect of the personal income tax system in urban China in 2011 (Du and Zhang 2018). As indicated in column D, the Gini index is significantly different before and after standardization based on bootstrapped standard errors,[3] meaning that changes in earnings homogamy in 1988–2013 made a statistically significant contribution to the growth of between-couple inequality.

Using Eq. (2), the overall contribution (i.e., the .01 Gini index point) can be decomposed into a sum of the separate contribution made by each individual couple. The contributions of individual couples within the same husbands' earnings decile are then totaled. The figures from columns A–D in panel b of Table 1 sum exactly to the numbers in panel a of Table 1 within the same column. Column E in panel b displays the proportional contribution of changes in earnings homogamy between each decile of husbands and their wives to the overall impact of changes in earnings homogamy. This column shows that 68% of the overall impact is due to changes in homogamy between the top 20% of husbands and their wives. On the contrary, the negative percentages in the top three cells in column E in panel b indicate that the changes in earnings homogamy between the bottom 30% of husbands and their wives actually equalized the couple earnings distribution, confirming the descriptive finding that the shifting pattern of earnings homogamy in urban China was nonlinear across the earnings distribution. Bootstrap significance levels reported in column D in panel b indicate that the decile-specific impact of changes in homogamy on inequality were (marginally) statistically significant only in the upper five deciles and the bottom decile.

Many previous studies focus on the U.S. context and use the CV^2-based decomposition. To put the findings into this context, I apply data from both urban China and the United States and repeat the previous decomposition analysis but use CV^2 to measure inequality. The numbers in Table 2 can be interpreted similarly to those in column E of Table 1. For urban China, the overall impact (10.62%) is larger than that reported

[3] I applied internal scaling to 100 bootstrap replicate weights to account for the stratified sampling strategy of CHIP (Rao et al. 1992). Then I calibrated the bootstrap weights (Shao 1996) to match the poststratification weights of CHIP suggested by Song et al. (2013). For a review of the bootstrap methods, see Hao and Naiman (2010).

Table 1 Decomposition of trends in earnings inequality (Gini) between couples due to changes in earnings homogamy

	Observed 1988	Observed 2013	Standardized 2013	Observed Change	Standardized Change	Contribution (%)
	A1	A2	B	C (= A2 – A1)	D (= B – A1)	E (= (C – D) /C)
a. Total						
	.1451	.3102	.2999	.1651	.1549*	6.20
b. Husband's Earnings Decile						E_k (= (C – D) / (0.1651 – 0.1549))
1	.0183	.0338	.0350	.0156	.0167†	−10.98
2	.0138	.0276	.0276	.0138	.0138	−0.03
3	.0122	.0246	.0250	.0124	.0128	−3.94
4	.0115	.0237	.0232	.0121	.0117	4.21
5	.0110	.0229	.0225	.0119	.0115	3.50
6	.0113	.0239	.0233	.0126	.0112†	6.18
7	.0116	.0252	.0240	.0135	.0124*	11.27
8	.0127	.0292	.0270	.0165	.0143*	22.07
9	.0157	.0368	.0351	.0212	.0194†	17.26
10	.0269	.0625	.0573	.0355	.0304*	50.44

Note: Significance levels (H_0: C – D = 0) are based on bootstrapping of 100 replications.

†$p<.10$; *$p<.05$

by the Gini-based decomposition, mainly because the decomposition based on CV^2 significantly downplays or ignores the equalizing impact of the changing homogamy between the bottom 30% of husbands and their wives, as shown in Table 2. Compared with Gini, the CV^2-based decomposition downplays the inequality impact of changes in homogamy near the bottom of the earnings distribution because CV^2 adopts a larger inequality-aversion parameter α than Gini. As shown in Eq. (1), α equals 1 for Gini and 2 for CV^2. When $\alpha = 2$, large values of the pairwise earnings differences, which usually involve high earners, are squared and thus become especially influential in determining the overall level of CV^2. The pairwise earnings differences among middle- and low-earners become relatively less influential.

In the United States, changes in earnings homogamy contributed 14.35% of the observed increase in the CV^2 of between-couple earnings inequality, similar to that reported by Gonalons-Pons and Schwartz (2017). Of this overall impact, 58% was attributable to changes among couples involving the top 20% of husbands and 19% to couples involving the bottom 20% of husbands; changes among couples involving the middle 60% of husbands contributed only 23%. As in urban China, the increasing earnings homogamy among high earners is the main driver behind the overall impact in the United States.

The main results of Table 1 and 2 are plotted in Figure 5. The dashed line $y = 10\%$ represents the linear or homogeneous assumption that changes in earnings homogamy at different levels of earnings make equal or homogeneous contributions to between-couple earnings inequality (i.e., the overall impact is evenly distributed across deciles,

Table 2 Proportional contribution of changes in earnings homogamy between each decile of husbands and their wives to the overall impact of changes in earnings homogamy to between-couple earnings inequality (CV^2)

	Overall	Husband's Earnings Decile										
		1	2	3	4	5	6	7	8	9	10	Total
Urban China	10.62	–0.76	6.31	3.05	6.97	5.39	5.81	5.40	10.79	12.63	44.43	100
United States	14.35	10.15	8.57	2.34	3.20	4.27	2.87	5.07	5.86	12.89	44.78	100

$y = 100\% / 10 = 10\%$). Apparently, this assumption does not fit the empirical pattern in either the Chinese or the U.S. data.

The Mechanical Relationship Between Economic Homogamy and Between-Couple Inequality

It remains unclear why the increase in earnings homogamy among high earners has such a disproportionately large impact on the earnings inequality between couples. Figures 3 and 4 offer one plausible explanation: earnings homogamy increased more among high earners in both contexts. However, this is unlikely to be the only reason. As illustrated in panels c and d of Figure 4, the magnitude of increases in earnings homogamy between the top 10% of husbands and the top 10% of wives was much larger in the United States than in urban China. However, according to Table 2, in both contexts, the proportional contribution of increases in earnings homogamy between the top 10% of husbands and their wives is almost identical (44%). This suggests another potential explanation: increases in earnings homogamy among high earners may always have the largest impact on between-couple inequality, *ceteris paribus*. In this section, I use simulations to ascertain the plausibility of the second explanation.

The simulations use three artificial data examples as summarized in Table 3. Each data set consists of 5,000 couples, in which the husbands' earnings are lognormally distributed with a mean of 1 and standard deviations of 0.7, 0.5, and 0.05, respectively. The wives' earnings are also lognormally distributed with a mean of 0.6 and standard deviations of 0.4, 0.3, and 0.03, respectively. With only two parameters (mean and standard deviation), the lognormal distribution provides a simple right-skewed distribution that approximates typical income distributions in real life (Cowell 2011). A larger standard deviation indicates that the distribution is more right skewed and dispersed over a wider range—that is, more unequal.[4] Among the three data sets, husbands' and wives' earnings distributions are most unequal in Data 1, modestly unequal in Data 2, and least unequal in Data 3. Husbands' and wives' earnings distributions in Data 3 are deliberately specified as being unrealistically equal (their Gini indices are close to 0). On the contrary, Data 1 is closest to the real-life situation. As Table 3 shows, the Gini indices

[4] I do not further explore the separate effect of right-skewness and range.

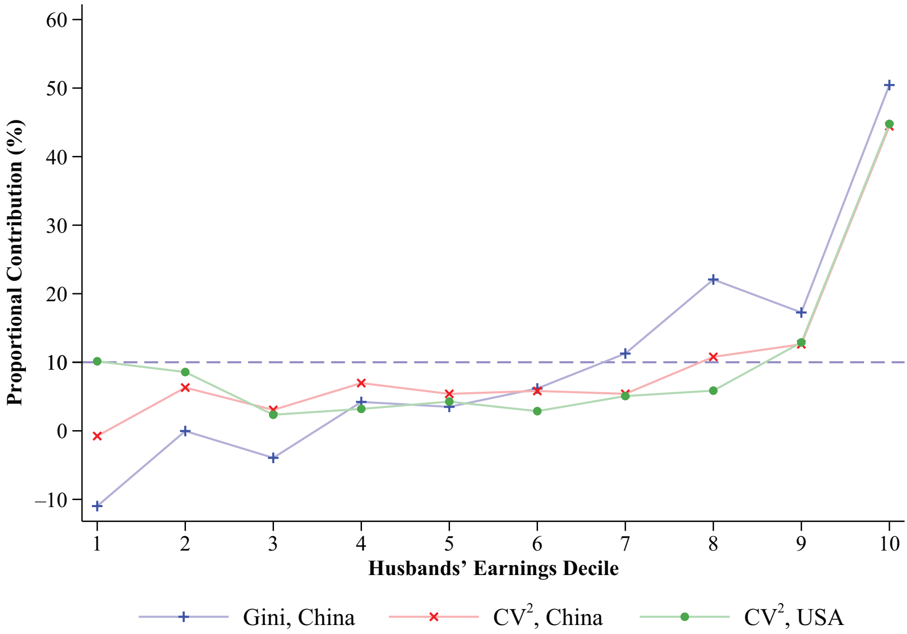

Fig. 5 Proportional contribution of changes in earnings homogamy between each decile of husbands and their wives to the overall impact of changes in earnings homogamy to between-couple earnings inequality. The figure is a visualization of Table 1 (column E, panel b) and Table 2.

of the gender-specific earnings distributions in Data 1 resemble those in urban China in 2013 and are lower than those in the United States in 2013.

I start by randomly matching husbands and wives within Data 1, 2, and 3, forming my three baseline data sets. Next, I generate five new data sets from each of the three baseline data sets. In each new data set, I rematch the ith ($i=1, 2, \ldots, 5$) quintile of husbands and their wives,[5] assuming perfectly positive matching on their earnings while preserving the baseline pattern of random matching among couples in the other four quintiles. I end up with six data sets: one baseline data set of randomly matched couples and five new data sets of *partially* positively rematched couples. I compute the difference in between-couple inequality between the baseline data set and each of the five new data sets. This gives me a quantitative assessment of the impact of increases in earnings homogamy (from random matching to perfect homogamy) at different parts of the earnings distribution on the level of between-couple inequality.

Figure 6 displays the impact of the quintile-specific positive rematching on three outcomes: between-couple inequality measured by Gini and CV^2, and spouses' earnings correlation measured by Pearson's correlation coefficient. My simulations are conducted on 150 random matching data sets (i.e., 50 for each data example). Figure 6 shows the average of the estimated impact sizes across these data sets (within

[5] I am not rematching the ith quintile of husbands and the ith quintile of wives, but instead rematching the ith quintile of husbands and the wives who were previously randomly assigned to them. Because their wives were previously randomly assigned to them, their wives can come from any part of the wife's earnings distribution.

Table 3 Artificial data examples used in simulations

		Data 1, Most Unequal			Data 2, Modestly Unequal			Data 3, Least Unequal			Urban China 2013	United States 2013
	Mean	SD	Gini	CV^2	SD	Gini	CV^2	SD	Gini	CV^2	Gini	Gini
Husband	1.000	0.700	.347	0.512	0.500	.260	0.244	0.050	.029	0.003	.312	.423
Wife	0.600	0.400	.333	0.432	0.300	.263	0.259	0.030	.028	0.002	.426	.590

Note: Mean and SD are parameters of lognormal distributions.

each of the three data examples) given that the pattern varies little across samples. The *y*-axis represents the difference in the three outcomes before and after positive rematching. No matter in which quintile it is performed, change in between-couple inequality is always positive, meaning that growth in earnings homogamy always increases between-couple inequality.

Figure 6 contains three new findings. First, panels a and b suggest that the impact of increases in earnings homogamy on between-couple inequality is far from linear or homogeneous. As long as there is some degree of inequality in husbands' and wives' marginal earnings distributions (i.e., when Data 1 [solid line] and Data 2 [dashed line] are used), positive rematching increases inequality more when it happens in the top quintile than when it happens in the middle and low quintiles. Because earnings distributions in real life are always unequal, I can conclude with confidence that increases in earnings homogamy among high earners always have the largest impact on inequality, *ceteris paribus*.

More importantly, the shapes of the three lines in panels a and b of Figure 6 reveal that the cause behind the nonlinearity of the impact of earnings homogamy on inequality is that the marginal distributions of husbands' and wives' earnings are already unequal. When the simulations are based on Data 3, which features an unrealistic scenario of high equality in the marginal earnings distributions, the disproportionality of the large impact of earnings homogamy among high earners disappears (see the dash-dotted lines).

Second, the degree of the disproportionality of the large impact of earnings homogamy among high earners varies across inequality measures. When simulations are based on Data 1 (the solid line), the disequalizing impact of positive rematching in the top quintile is 993% larger than that in the bottom quintile if inequality is measured by CV^2 (panel b of Figure 6) but only 47% larger if inequality is measured by Gini (panel a of Figure 6). This explains my previous empirical finding that in urban China, the equalizing impact of the declined earnings homogamy among low earners is largely ignored when inequality is measured by CV^2. Panel c of Figure 6 shows that the correlation coefficient behaves very similarly to CV^2 and is also much more responsive to increases in earnings homogamy among high earners. These findings, however, do not imply that CV^2 or the correlation coefficient are bad measures. Which measure to use depends primarily on context. The finding that CV^2 and Gini differ in their susceptibility to earnings homogamy among high earners indicates that objective inequality measures always embody subjective assumptions about why an income distribution is more "unequal" than another (Atkinson 1970).

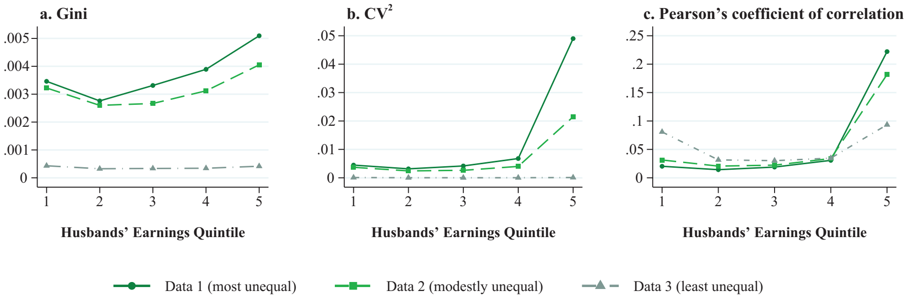

Fig. 6 Quantile-specific impact of positive rematching on between-couple inequality based on simulation results. The *y*-axis represents the difference in the quantity specified in the subfigure title before and after positive rematching. Simulations are based on three hypothetical data sets in which the marginal earnings distributions differ in their degree of inequality.

Third, Figure 6 also reveals that the *amount of inequality* between couples that can be potentially generated by increases in earnings homogamy depends on the overall earnings inequality among husbands and wives. As indicated in panels a and b of Figure 6, the absolute level of the solid line is always higher than the dashed line, and the dashed line is higher than the dash-dotted line. This pattern implies that the impact of earnings homogamy on between-couple inequality is multiplicative: increases in earnings homogamy increase between-couple inequality, and their disequalizing impact is stronger in societies where earnings are more unequally distributed among married men and women. The implication is that it makes little sense to compare the importance of earnings homogamy with between-couple inequality across societies or periods without taking into account the difference in the overall earnings distributions between societies or periods (Kenworthy 2007). In the extreme scenario represented by Data 3, in which the earnings distributions among husbands and wives are very equal, even a drastic transition from random matching to perfect homogamy generates little inequality between couples. This is not because the change in the degree of homogamy is not large enough, but because there is not sufficient inequality for positive sorting to amplify.

Discussion

This study examines the impact of changing earnings homogamy on earnings inequality between married couples. The literature recognizes the impact of earnings homogamy on between-couple inequality as a compositional effect: if more couples have two high-earning or two low-earning partners (i.e., increasing earnings homogamy), the earnings inequality between married-couple families will escalate, even if there is no change in the earnings inequality among individuals (Schwartz 2013).

In this article, I first evaluate the overall impact of the rise in earnings homogamy to the recent upturn in earnings inequality between married couples in urban China in 1988–2013. The overall impact ranges from 6% to 11%, depending on the measures used. What is new to this analysis is that I disentangle the overall impact by husbands' earnings decile using the iGini method proposed in Liao (2019). It turns out that 57% to 68% of the overall impact is driven by changes in earnings homogamy between the top 20% of husbands and their wives, and the remaining portions of the overall impact are sparsely distributed among the bottom 80% of couples. I find the same pattern by replicating the analyses using data from the United States. The overwhelmingly large impact of increases in earnings homogamy among high earners on between-couple earnings inequality can be accounted for in two ways. First, earnings homogamy may have increased more among high earners in both contexts. Second, all else being equal, increases in earnings homogamy among high earners mechanically contribute more to earnings inequality between couples than similar increases among middle or low earners. I find support for both explanations.

This article contributes to the literature in three ways. First, the mechanical pattern of the earnings homogamy-inequality association reveals a hidden yet important aspect of the relationship between marital homogamy and family economic inequality that has received little attention in previous research. Many previous studies have focused on increasing marital homogamy by education and its impact on family inequality. Economic resources, such as income, differ from education in that they always follow a highly right-skewed distribution. This feature leads to the mechanical pattern that, all else being equal, increases in homogamy among high earners would always be disproportionately influential in shaping the level of between-couple inequality. This mechanical pattern clarifies and extends the key theoretical intuition that motivates the body of literature on economic homogamy and inequality. Economic homogamy is important because as "spouses become more economically similar, inequality among married couples may rise because marriages are increasingly likely to consist of two high- or two low-earning partners" (Schwartz 2010:1525). Now it is clear that rising economic homogamy among high earners potentially plays a much larger role because it is intrinsically more detrimental to the economic equality between married-couple families than increasing economic homogamy among middle or low earners.

A second mechanical pattern is that increases in income homogamy produce more income inequality between couples in societies where incomes are more unequally distributed among married men and women. This finding has important policy implications. Some may argue that studies on the impact of income homogamy on between-couple inequality produce no policy implications because public policies should not be used to affect homogamy. When an economic elite marries another economic elite, they are simply exercising their right to personal liberty, which must be guarded against state intrusion, even if such behavior may negatively affect other people (Nozick 2013). However, my findings imply that although the strong tendency toward income homogamy among top earners may not be subject to policy intervention, its undesirably large impact on between-couple inequality can be mitigated by progressive policies even if such policies aim only to reduce the overall income inequality among individual men and women (e.g., antitrust enforcement, as discussed in Manduca 2019). As shown in panels a and b of Figure 6, if incomes could be more equally distributed among individual husbands and wives, even dramatic increases in income homogamy among high earners would generate much less inequality between couples.

Third, although in Western industrial countries an increase in female labor supply is accompanied by increases in the association between spouses' earnings (Esping-Andersen 2009), the case in urban China shows that a decline in female labor supply may not lead to declines in the association between spouses' earnings. As more women retreat from the labor market, the overall level of the association between spouses' earnings in urban China has not declined but has become similar to that in southern European countries, where the overall level of female labor supply is relatively low and yet the earnings homogamy among high earners is strong (Esping-Andersen 2007; Fiorio and Verzillo 2018). Nevertheless, the trajectories in urban China are unique in that earnings homogamy among low earners have somehow declined.

This article has several limitations. First, I am unable to show detailed patterns of earnings homogamy within earnings decile because of limited sample size. Second, because of space constraints, I do not show how changes in wives' employment have affected the trends in between-couple inequality. Third, the two inequality measures used in this article summarize the income distribution into a single number. I hope to consider the full income distribution in future research.

In summary, this article shows the merit of the quantile-based tradition in the literature of income inequality (Liao 2016). Future studies on the relationship between family structure and economic inequality could benefit from the quantile-based approach. The new empirical findings cannot be made without innovatively describing the form of the homogamy-inequality connection by income level, which reaffirms the value of the tradition in demography that a clearer description of the form of a sociodemographic relationship is fundamental to understanding it (Montez et al. 2012). ■

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