Essays on Labor Economics

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Essays on Labor Economics

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ABSTRACT OF THE DISSERTATION

Essays on Labor Economics

by

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Doctor of Philosophy in Economics
University of California, Los Angeles, 2020
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This dissertation contributes towards our understanding of Labor Economics and Applied Econometrics. It consists of three chapters. The first two chapters shed light on the determinants of female labor supply behavior by connecting theory to household-level data. The third chapter studies the nonlinear generalized method of moments (GMM) in dynamic panels and its application to value-added models of learning.

In Chapter 1, I propose that the rising sex ratio (number of males per female) imbalance has been an important factor in the recent feminization of rural-to-urban migration in China. To establish this connection, I first develop a three-player noncooperative household model in which both the parents and the daughter contribute time or money to improve the well-being of sons. The local sex ratio can affect the players' choices via two channels: either by influencing the preference towards sons, or by imposing negative impact on sons' welfare due to intensified marriage market competition. My model predicts that daughters are more likely to participate in migratory work when the local sex ratio is higher. Drawing on data from Rural-Urban Migration in China Survey, I then test the hypothesis by comparing unmarried rural women with brothers and those without brothers when conditioning on family size. My identification strategy exploits the exogenous variation in the number of brothers a rural woman has that comes from the randomness in parental sibling structure. I show that an increase in the local sex ratio significantly raises the probability of becoming a migrant worker for unmarried rural women who have brothers, while no significant effect is

observed among those without brothers. The positive link is stronger for rural women who have a larger number of brothers or whose brothers are relatively younger. I also discover that around 40% of the increase in rural female labor migration rate from 1990 to 2000 could be explained by the changes in the sex ratio. I further find evidence in favor of the marriage market pressure mechanism.

Chapter 2 (joint work with Zhongda Li) examines the intergenerational determinants of women's labor force participation decision. Existing studies have established a positive correlation between a married woman's work behavior and her mother-in-law's. Such linkage is attributable to the profound influence of maternal employment on son's gender role preferences or household productivity. In this chapter we investigate the relative importance of the two potential mechanisms using the Chinese survey data. We show that a substantive part of the intergenerational correlation is left unexplained even if we control for the husband's gender role attitudes. Instead, we find that the husband's household productivity is more crucial in the wife's work decision, suggesting the dominance of the endowment channel over the preference channel.

Chapter 3 develops a novel framework for constructing nonlinear moment conditions in dynamic panel data models. I demonstrate that the nonlinear GMM estimator considerably mitigates the classical weak identification problem arising from two data generating processes: (i) the autoregressive parameter is close to the unit circle; (ii) the ratio of variances of individual heterogeneity and idiosyncratic errors diverges to infinity. I further derive analytical expressions for the bias term of the linear and nonlinear GMM estimators, and show that the use of nonlinear moments results in smaller finite sample bias. In simulation studies, the nonlinear GMM estimator performs well compared to both the difference and system GMM estimators. As an empirical illustration, I estimate the effect of class size reduction and private school attendance on student academic achievement using a value-added model with learning dynamics.

The dissertation of Lu Liu is approved.

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2020

To my parents for their love and support during this PhD journey

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Finally, I owe my deepest appreciation to my parents for their unconditional love and strong support throughout the journey of my graduate studies.

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CHAPTER 1

Sex Imbalance and Female Labor Migration in Rural China: Marriage Market Pressure or Son Preference?

1.1 Introduction

The urbanization process in China is characterized by massive volume of internal migration. During the period between 1982 and 2016, the number of individuals living outside their hometown has increased dramatically from 6.6 to 245 million, reaching a level equivalent to roughly 18% of the total population. Particularly, young migrants who move from rural to urban areas to seek employment are recognized as a dominant contributor to the unprecedented rise in recent migration flows. As reported in the latest survey of China's National Bureau of Statistics (NBS), rural-to-urban migrants account for over 68% of the migrant stock in 2016, of which the majority were born after 1980. Another noteworthy aspect of the current migrant population is that it has shifted from a male-dominated structure to one that is nearly gender-balanced (Chiang et al., 2015). Overall, women constitute almost half of all migrants nationwide, and their fraction in the rural migrant workforce has been steadily increasing. While the economic motivation and impact of rural-to-urban migration as a whole have been intensively studied, relatively little is known about the migration behavior of rural females.

What factors are responsible for the increasingly important role that women play in China's rural-to-urban migration? The answers to this question are essential for understanding the dynamics of internal migration as well as its implications for economic development. One of the few explanations proposed is that the expansion of non-agricultural industries, especially manufacturing and services sectors, leads to the rapid surge in rural women's migration (Lu and Xia, 2016). The export-oriented firms in these industries prefer to employ young rural female migrant workers who are willing to work long hours for low pay as cheap and flexible labor source (Dittmer and Liu, 2006). Another explanation regards women as subordinate to men in rural-to-urban migration as many of them follow their husbands to urban areas (Lina, 1999).

In this paper, I suggest a new and complementary mechanism that shapes the contemporary female migration patterns in rural China. Specifically, I put forward a hypothesis that the severe male-biased sex imbalance is a critical factor behind the increasing labor migration of young rural females. Such relation might be interpreted as the influence of cultural preference towards sons on the daughter's migration behavior in a rural household. I posit that, for unmarried rural women who have brothers, their migration decisions could be determined by how much they care about their brothers. When they are more concerned about the male siblings' well-being, as reflected by a higher sex ratio (defined as the number of males for every female), they would exhibit a greater propensity to participate in migratory work. Through labor migration, these rural women are able to raise their income and thereby invest more in their brothers.

An alternative and also more interesting pathway is through marriage market pressure. In China, social norms and marriage traditions typically require the groom's family to pay a bride price and purchase a house for the newlywed. As the sex ratio rises, the intensified competition for brides can inspire parents to accumulate more wealth in hopes of improving the marriage market prospects of their sons (Wei and Zhang, 2011a). The marriage market squeeze may also affect the earning incentive of the daughter in a rural household. Previous studies have established that compared to men, women place a greater emphasis on the need to support families economically when deciding whether to work outside (Chiang et al., 2015; Lina, 1999). I claim that, in response to the ever-rising sex ratio, young peasant women with a male sibling are more likely to migrate for work in order to share the heavy burden of financing their brothers' weddings. It is notable that labor migration does not undermine the marriage market conditions of rural women or cause a delay of their own marriage[1].

[1]For most rural individuals, out-migration is temporary and only a specific stage of their working life. It

The rural female migrants in fact tend to have larger search pools with a higher chance of finding a better partner. For rural women with no brothers, the effect of sex imbalance is ambiguous. On the one hand, they have a weaker incentive to become a migrant worker as they anticipate a higher level of household wealth from their future husbands. On the other hand, their willingness to work outside the home might not decline if they believe that the wife's bargaining power within a family is positively associated with her relative wealth position before marriage.

I develop a theoretical model that captures the main elements of my stories in a simple way. My model utilizes a noncooperative household framework in which both the parents and the daughter make decisions about consumption, leisure and son investment. The well-being of the sons is modelled as a public good that enters the utility functions and depends on inputs of time and money contributed by the household members. To model the son preference channel, I augment the preference weights on son quality with the local sex ratio. This assumption is consistent with the idea that the local sex ratio reflects the regional common culture of son preference adopted by the household. In my model of the marriage market competition channel, the preference for son quality no longer differs by the local sex ratio across regions, but the well-being of the sons is now assumed to be negatively related to the local sex ratio. Both specifications are capable of generating a positive link between the local sex ratio and the daughter's labor migration behavior. My model also suggests that, when both channels are present, the daughter's migratory labor supply are more sensitive to changes in the extent of marriage market competition in most scenarios.

In an effort to test the model predictions, I primarily draw on data from Rural-Urban Migration in China (RUMiC) Project and China Population Census. The RUMiC survey elicits detailed information on individual migration outcomes, including current migration status and former migration experience, and also collects rich data on the respondent's demographic characteristics and family background. Two features of the survey are important

is common for rural migrant workers to return to their home villages after spending several years working in the urban labor market. Even during their migration period, they still move back to the origin rural areas from time to time.

for my study. First, it contains the county identifier for each respondent, which allows me to merge the county-level sex ratios calculated from the census onto the survey data. Second and most relevant for my purpose, it includes every household member as a respondent. As such, I am able to exploit the specific sibling information to investigate the mechanisms behind the relationship between the rural women's work migration outcomes and the sex ratio imbalance.

The analysis uncovers remarkably distinct labor migration responses to the local sex ratio among rural women with different sibling structures. I start with the observation that growing up in a county with a more skewed sex ratio indeed significantly enhances the probability that an unmarried rural woman who has a male sibling participates in migratory work, even after controlling for many other background characteristics of the woman and the place of her origin that may affect her migration decision and that may drive the positive correlation. Depending on model specifications, an increase in the local sex ratio by 10 percentage points raises the likelihood of becoming a migrant worker by 4.35-6.84 percentage points for rural women with brothers, which corresponds to a 22-34% increase in the labor migration rate (the national average labor migration rate among this group of women is around 20%). Nonetheless, I do not find any significant effect of the local sex ratio on the migration choice of rural women who do not have a brother.

I also report several additional results. I first demonstrate that the local sex ratio imbalance is much more likely to propel rural women having multiple brothers to migrate for work relative to those who have a single brother. I then examine whether the local sex ratio effect varies by birth order. Consistent with the traditional norm that elder siblings undertake the responsibility of supporting younger siblings, I find that rural women with only younger brothers react more sensitively to changes in the local sex ratio than those with only elder brothers. Moreover, the effect size increases drastically as the age gap widens.

I conduct a variety of sensitivity tests to ensure that my main results are not driven by other factors. First, I show that the estimated coefficients retain sign and significance when I use alternative definition of labor migration. Second, my results are robust to different measures of local sex ratios for both marital and premarital age groups. Another concern is that the male-biased sex ratio may reduce rural women's migration intention through improving their relative bargaining position in the marriage market. To alleviate this issue, I restrict my sample to younger cohorts of rural women and the results are unaltered. In addition, one might also worry that the comparison between rural women with brothers and those without brothers could be contaminated by unobservable household characteristics. I allow for the potential endogeneity of sibling structure by taking advantage of the randomness in sibling gender composition of the parental cohorts. Furthermore, the local sex ratio might be confounded with some regional unobservables that likely affect rural women's labor migration outcomes. In response to this potential threat, I attempt to instrument the local sex ratio using the exogenous variations in fertility penalty across regions and over time. The instrumented results lead me to the same conclusion.

In addition to the household-level evidence, I next evaluate how the changes in the sex ratio affect the changes in rural women's labor migration rate over time at the prefecture level. Conditional on a series of regional characteristics and time fixed effects, I show that a 10 percentage point increase in the local sex ratio is associated with a 2.29 percentage point increase in the proportion of unmarried rural women engaging in migratory work. To put this into perspective, in my sample, the average female labor migration rate across prefectures rises from 2.1% in 1990 to 9.9% in 2000, in company with an increase of the sex ratio from 1.044 to 1.175. Taken together, my results indicate that the rising sex ratio could explain around 40% of the increase in rural female labor migration rate from 1990 to 2000.

Before concluding the study, I proceed to explore the potential channel through which the local sex ratio imbalance triggers female labor migration in rural areas. By performing a series of empirical exercises, I find evidence in favor of the marriage market mechanism. Specifically, I show that the sex ratio for older cohorts in the local population, which is unlikely to be indicative of the current or future marriage market conditions, has very small and insignificant effect on rural women's incentive to migrate. In addition, there appears to be no significant relationship between the local sex ratio and labor migration outcomes among rural women who have only married brothers. I also discover that having a migrant sister mitigates the negative impact of male-biased sex ratios on the probability of being married for rural men. Finally, I find that the local sex ratio effect is mainly driven by increases in the marriage-related expenditure and housing price. Overall, I consider my findings as supportive of the idea that marriage market competition channel is relatively more important.

I consider my paper as making three contributions. First, my findings contribute to a growing literature that examines the consequences of the sex ratio imbalance. Several prior papers document that the marriage market pressure generated by the skewed sex ratios has important impacts on household behavior along different dimensions. For example, Wei and Zhang (2011a) find compelling evidence that parents with a son tend to raise their savings rate competitively in regions with a higher sex ratio. In a similar spirit, Wei and Zhang (2011b) show that the shortage of marriageable females could stimulate men and parents with a son to work longer hours, become more entrepreneurial and more willing to take a relatively dangerous job in exchange for higher pay. In contrast to the competitive wealth accumulating motive, Grier et al. (2016) demonstrate that unmarried men residing in areas with an unbalanced sex ratio purchase more expensive and luxury vehicles as ways to signal socioeconomic status in the marriage market. Compared to their work, I focus on unmarried rural women who do not directly face the pressure of finding a mate, and show that the sex ratios unfavorable to males also create incentives for rural women with brothers to engage more in earning activities.

My second contribution is to the large literature that seeks to understand the determinants of rural-to-urban migration in developing countries (e.g. Morten, 2019; Munshi and Rosenzweig, 2016; Zhao, 1999). In general, rural workers move in response to income differentials between urban and rural sectors (Lewis, 1954; Todaro, 1969). In addition to the direct economic gains, recent research has highlighted the role of non-economic factors, such as reduction in migration barriers and access to social networks, in facilitating internal migration (Beegle et al., 2011; Fan, 2019). However, few of these studies rigorously investigate the forces driving rural women's mobility behavior. I add to this literature by providing new evidence that changes in the marriage market conditions for the brothers motivate rural women to migrate out of their home villages. My analysis can serve as a gendered assess-ment of rural-to-urban migration, suggesting that family considerations are central to rural women's labor migration decision.

My work is also related to a literature in family economics and macroeconomics that is interested in intrahousehold decision making and how this matters for macroeconomic outcomes (see Doepke and Tertilt, 2016; Greenwood et al., 2017, for excellent reviews). In particular, my theory builds on the separate spheres framework advanced by Lundberg and Pollak (1993) where spouses adhere to traditional gender division of labor. Unlike the usual two-player set up, I consider the extension to a three-player noncooperative game which allows for the interactions between the parents and the daughter. The sons are deemed as household public good to feature either son preference or collectivistic family values in Asian societies. My model indicates that the prevalence of this type of families combined with highly skewed sex ratios can help explain the recent feminization of China's rural-to-urban migration.

The remainder of the paper is organized as follows. Section 2 offers an overview of the background on sex imbalance in China. Next, Section 3 documents a series of descriptive facts for my hypothesis. Section 4 presents the theoretical framework that formalizes my empirical analysis, before Section 5 describes the data. Section 6 discusses the empirical strategy, and in Section 7 I report the main results. Subsequently, Section 8 provides further evidence on the underlying mechanisms that connect local sex ratios and female labor migration behavior. Finally, Section 9 concludes.

1.2 Background on Sex Imbalance in China: Causes and Consequences

The extraordinarily male-skewed sex ratios in a number of Asian countries have attracted considerable interest from academics and policymakers, dating back to the pioneering work of Sen (1990, 1992) that famously developed the concept of "missing women". In his writings, he estimated that more than 100 million women were demographically missing from the world's population in the early 1990s. This observed deficit is a direct consequence of both prenatal sex selection and postnatal excess female mortality among almost all age cohorts, which largely stem from parents' desire for sons and gender bias in the allocation of survival-related resources respectively. The vast majority of the missing women are from East and South Asia where favoritism towards males is deeply embedded in traditional culture. Existing evidence suggests that parental preferences discriminating against girls play an overwhelmingly predominant role in determining the sex imbalance in East and South Asia (Anderson and Ray, 2010; Gupta, 2005). Among nations in this region, the case of China warrants special attention for two reasons: first, China is a large developing country with the biggest population and most severe sex ratio distortion; second, the recent gender imbalance in China is not only caused by the persistent son preference but also a result of policy interventions.

1.2.1 Son Preference and One Child Policy in China

In China, son preference is a pervasive phenomenon with a long history. Culturally, the Confucian values of hierarchy perceive men as superior and women as subordinate in the patrilineal kinship system. Sons, rather than daughters, are expected to continue the family line, tend ancestral shrine and inherit family properties (Li and Cooney, 1993). Economically, sons are more likely to become the main laborers for the family and remain within the household to provide elderly support for parents.

In spite of this longstanding preference for sons, the sex ratio has been maintaining at a relatively low level until the 1980s. According to the census data, in 1982, the sex ratio at birth in China is around 1.08, which is only slightly higher than the biologically natural sex ratio of 1.05. However, by the end of 2010, the sex ratio at birth has soared to 1.18, and in some provinces this ratio even exceeds 1.25. Such incredible and abnormal increases in sex ratios have been attributed to the introduction of the well-known One Child Policy (OCP) in 1979. Under this policy, most of the Chinese residents are restricted to have only one child, and those who violate the policy by giving birth to unauthorized children could face heavy financial punishments and even loss of employment. Given the enormous cost for having multiple children, the Chinese parents appear to engage in the practice of sex selection, ranging from abandonment, to abortions and even infanticide, to ensure the birth of at least one son. In particular, the diffusion of ultrasound technology in the 1980s has made prenatal gender determination possible and inexpensive, giving rise to large-scale sex-selective abortions and a further deterioration in sex imbalance. Chen et al. (2013) demonstrate that about half of the increase in sex ratio at birth during the 1980s can be accounted for by the local access to ultrasound examinations.

1.2.2 Enforcement of One Child Policy

The OCP was initially designed to impose a strict one child limit for every couple. However, resistance to the policy was fierce in the vast rural areas where male children were strongly preferred to help with farm work and old-age support. In view of the difficulties during implementation, the central government relaxed the birth control regulations in some parts of China. Although the one-child-per-couple rule is still generally applicable nationwide, the enforcement of the policy has demonstrated considerable heterogeneity across localities, depending on the demographic and socioeconomic conditions (Gu et al., 2007; Hardee-Cleaveland and Banister, 1988; Zhang, 2017). First, the policy is more stringently implemented in urban areas than rural areas. Urban couples are subject to the one child fertility limit in most circumstances, whereas rural families are often allowed to have a second child, especially when their first child is a daughter. Second, Han Chinese are under tighter fertility control than ethnic minorities. Residents who belong to an ethnic minority group are permitted to have two or more children.

In addition, the localization of the OCP is also reflected by the variation in fertility fines across regions over time. Without violating the general guidelines of controlling population growth, the local governments are granted the authority to set the monetary penalties for above-quota births. The fines are usually levied as one-time punishment, ranging from 5% to 500% of the annual income. Empirical evidence shows that higher fine rates are associated with a lower fertility level while increases the proportion of males in the population

(Ebenstein, 2010).

1.2.3 Consequences of Female Deficit

The growing sex imbalance in China has aroused widespread concerns over its adverse social and economic impacts. The most direct consequence is the male marriage squeeze in the marriage market. Ebenstein and Sharygin (2009) show that men outnumber women by 22 million for cohorts born between 1980 and 2000, and about 10.4% of these additional men are expected to fail to find spouses based on their simulations. The number of excess males will continue to grow, and by 2020 there will be a surplus of 29-33 million young males who are forced to remain single (Hudson and Boer, 2002). The surplus males who are unable to marry themselves often feel socially isolated, have a lower level of life satisfaction and high rates of depression (Attané et al., 2013; Li et al., 2014). The rising competition for wives also leads to an increase in marriage expenses for men, which in turn imposes a heavy financial burden on families with a son (Jin et al., 2013). To prepare for a wedding, the groom's family is often responsible for purchasing a new house for the newlyweds, paying a high bride price and bearing the bulk of the cost of holding a wedding banquet. As revealed by a survey conducted in 2009 over 364 villages nationwide, the total marriage expenses in rural areas amount to 16-28 times of a rural household's annual net income (Jiang et al., 2015). Confronted with the skyrocketing marriage costs, parents with a son, especially those living in regions with a more skewed sex ratio, increase household savings rate competitively (Wei and Zhang, 2011a), and tend to consume more alcohol and tobacco to cope with the marriage market pressure (Chen, 2017).

The negative effects of sex imbalance are not confined to the marriage market. Evidence suggests that the presence of huge population of involuntary bachelors may pose a serious threat to public security. It is well documented that single men exhibit a higher antisocial tendency and have a greater propensity to commit crimes than married men at the same age living stably with spouses (Horney et al., 1995; Mazur and Michalek, 1998). As sex ratio grows, there will be fewer men who are able to enter into marriage and these excess men are an important source of social instability (Hudson and Boer, 2002; Li et al., 2014). Edlund et al. (2013) find a positive and significant relationship between sex ratio and crime in China. Complementing their study, Cameron et al. (2017) show that the primary avenue through which the sex ratio raises criminal activities is the direct pressure on men to improve their financial attractiveness with the intention of finding a wife. What makes matters worse is that the large demand for women has spurred various crimes that infringe women's personal safety and human rights, including sexual assault, forced marriage, forced prostitution (Banister, 2004) and female trafficking (Zhao, 2003). Furthermore, highly distorted sex ratios are also detrimental to public health. The rise in the share of unmarried men in the population provides a significant impetus for the expansion in sex industry, exacerbating the spread of sexually transmitted infections (Ebenstein and Sharygin, 2009, 2016).

Apart from various adverse consequences of sex imbalance, there have been a few attempts to examine the causal relationship between male-biased sex ratios and female labor market outcomes. Most of these studies focus their attention on female labor force participation: they find that high sex ratios have a large negative effect on women's propensity to work due to the increased female bargaining power in the marriage market (Angrist, 2002; Raphael, 2013). However, considerably fewer efforts have been devoted to exploring how female migration patterns correspond to changes in sex ratios. In this paper, it is my goal to estimate the causal impacts of an increase in sex ratio on the likelihood of female labor migration in China. I believe that a thorough analysis of this link will contribute to our understanding of labor market dynamics in the context of China's great internal migration and unbalanced sex ratios.

1.3 Descriptive Evidence

The main goal of this section is to present a series of descriptive facts to set the stage for the theoretical and empirical analysis using the data from China Population Censuses. I start by describing the evolutionary trends of both the sex ratio and the female migration rate in China. I then decompose female migration according to self-reported reasons, and document the positive correlation between local sex ratios and rural women's migratory work behavior. I highlight the disparity in these patterns between rural women with brothers and those without brothers. Finally, I discuss the potential influence of migratory work experience on rural women's marriage market prospect. The model constructed in the next section attempts to provide possible channels formalizing the link from sex ratio imbalance to labor migration choice among rural women who have brothers. This relationship and the underlying mechanisms are subject to careful scrutiny in the subsequent empirical exercises that complete my paper.

1.3.1 Evolution of Sex Ratio and Female Migration Rate

Figure 1.1 plots the sex ratios by birth year for cohorts born between 1950 and 2010. Despite some short-term fluctuations, before 1990, the sex ratio at birth was kept at a relatively normal range of 100 to 110 boys per 100 girls. During the Great Famine[2] between 1959 and 1961, there has been a sudden and sharp drop in the sex ratio at birth. The declining proportion of male births, according to the adaptive sex ratio adjustment hypothesis[3], was largely a result of maternal malnutrition. In the mid-1960s, as the economy began to recover, the sex ratio at birth has gradually increased and stabilized at its natural level of around 1.05. This balance ended in the mid-1980s, and was followed by a long-term steady rise, resulting in over 120 males births for every 100 female births in 1999. The timing of the rise in the sex ratio at birth coincides with the implementation of China's OCP, indicating that fertility restriction might be the direct cause of the long-lasting sex imbalance.

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[2] The Great Famine is also called "Three Years of Natural Disasters" in China, which refers to the nation-wide famine taking place during the years between 1959 and 1961. Although the adverse weather conditions contributed to the famine, the key factor of this tragedy is the policy errors and economic mismanagement that accompanied the Great Leap Forward, a failed industrialization campaign from 1958 to 1962.

[3] The adaptive sex ratio adjustment hypothesis, proposed by Trivers and Willard (1973), predicts that mothers in good conditions tend to produce more male offsprings, whereas the reverse is true for mothers in poor conditions. The suggested reason is that male reproductive success is more variable and resource-sensitive than female reproductive success. While males in good conditions are found to outproduce females in comparable conditions, their reproductive returns fall substantially to near zero in poor conditions. To achieve optimal reproductive results, natural selection should favor maternal ability to adjust the sex ratio of offspring according to maternal ability to invest.

Figure 1.2 looks specifically at the evolution of both the sex ratio and the female migration rate for the youths who are between ages 16 and 20. Since the legal age of marriage for Chinese women is 20, the sex ratio for these cohorts captures the degree of marriage market competition among families with sons who are about to get married in the near future. The figure reveals strikingly similar trends in sex ratio and female migration rate.

In Figure 1.3, I break down the population of female migrants according to the self-reported reasons for migration. In the national population census surveys, the motives for migration are grouped into nine categories: (1) work or business, (2) job transfer, (3) job assignment, (4) study or on-job training, (5) move to live with relatives or friends, (6) marriage, (7) move with family, (8) relocation, and (9) others. As can be seen in Figure 1.3, the increasing female migration rate is due in large part to the rise in the fraction of labor migration. The proportion of young women who migrate to cities for work increases from less than 20% in 1990 to nearly 40% in 2010.

1.3.2 Cross-sectional Correlation between Local Sex Ratios and Female Labor Migration Rates

The time series plots in the previous subsection offers some preliminary evidence for the connection between the sex ratio and rural women's labor migration behavior. As an alternative exploration of the patterns, I next focus on cross-sectional comparisons. In particular, I compare the geographical distribution of the sex ratio to that of the share of young rural females who work outside the hometown. Figure 1.4 displays the relationship between local sex ratios and female labor migration rates at the prefecture level in 2005. As the figure shows, a higher local sex ratio for the premarital age cohort is associated with a larger proportion of young rural female migrant workers. Similar figures are obtained when I use the samples from the census conducted in 2000[4].

[4] The National Bureau of Statistics of China carried out a full population census every ten years at the year ended by 0 as well as an inter-census population survey between two full censuses at the year ended by 5. The latter is also known as the mini population census, or the 1% population sample survey. I mainly use the 1% sample survey in 2005 to establish the stylized facts based on two reasons. First, it provides more detailed personal information, including whether the respondent has brothers, from which I can draw

The central hypothesis in my paper is that the local sex ratio imbalance induces young rural women who have brothers, relative to those who do not have brothers, to participate more in migratory work. To see this, I first present the distributions of self-reported reasons for migration for the two groups of rural women in Figure 1.5. It is apparent from the figure that labor migrants constitute a much larger percentage of the migrant population for rural women having brothers than those having no brothers. While nearly 60% of the rural women with brothers report work or business as their primary reason for migration, less than 35% of their peers who do not have brothers give the same reason.

In Figure 1.6, I take a first crude look at the differential effects of sex ratio imbalance on the labor migration behavior for the two types of rural women. As depicted in the figure, in regions with a more skewed sex ratio, rural women appear to be more likely to migrate to urban areas for work regardless of whether they have brothers or not. Interestingly, I observe a considerably stronger positive relationship between local sex ratios and proportions of labor migrants among rural women with brothers than rural women without brothers. The pattern is consistent with my conjecture: as the local sex ratio increases, rural women with brothers have a greater incentive to migrate as a way of earning more to improve the competitiveness of their brothers in the marriage market. Through the influence of peers, sex imbalance may also raise the probability of labor migration for rural women without brothers. To further verify these correlations, I will perform formal regression analysis using more detailed micro-level household data.

1.3.3 Migratory Work Experience and Rural Women's Marriage Prospect

Some may argue that the scarcity of women could improve their relative bargaining position in the marriage market, which in turn reduces their incentive to migrate. Regarding this concern, it is important to stress that rural women's marriage market conditions will not deteriorate when they choose to work outside the hometown. On the one hand, due to the

a comparison between rural women with brothers and those without brothers. Second, the household survey data I use for the empirical exercises cover the sample period 2007-2008, which is closer to 2005.

barrier of the household registration system[5], the majority of internal migration in China is temporary rather than permanent. After spending several years working in the urban labor market, rural migrants exhibit strong tendency to return to their home villages, either getting married or settling down permanently. According to Wei and Zhang (2011a), 89% of the marriages in rural China are formed between men and women from the same county. This suggests that even if rural women migrate to urban areas in the earlier stage of their working life, most of them end up marrying a man who comes from their native place. On the other hand, rural female migrants seem to have larger marital search pools than their non-migrant peers. Based on the data from China Labor-Force Dynamics Survey (CLDS), rural women whose spouses are from a different county on average receive a higher bride price payment than those who have local husbands. In addition, they also match with higher-quality husbands who are better educated and who have higher annual income.

Another important question to ask is whether migratory work experience delays rural women's entry into first marriage. In regions with a surplus of males, the groom's family is expected to contribute a considerable amount of money to the bride's family as betrothal gift. If temporary labor migration causes a delay of rural women's marriage, then those who have brothers may be more inclined to remain in the local areas so that their families could receive the bride price payment earlier. Figure 1.7 depicts the survival curves of first marriage for female migrants and non-migrants. The figure shows that the phenomenon of illegal early marriage is relatively rare: less than 13% of the rural women have been ever married before the age of 20. After this point, the proportion of unmarried rural women plunges, and by age 22 over half of them have got married. While the marriage rate among female non-migrants appears to be slightly higher than female migrants between ages 15 and

[5] The household registration system in China was formally established in 1958 as a means of controlling population movement and preserving social stability. Under the relevant regulations, each citizen has to be registered in the location where he/she comes from and is classified as either agricultural or non-agricultural residents. The household registration status not only officially identifies where a person belongs to but also determines one's eligibility for state-sponsored goods and welfare. Before the mid-1980s, migration from one location to another is prohibited without the permission given by the local government. Although restrictions on internal migration have been loosened in recent decades, rural migrants in urban areas are still denied access to good jobs, subsidized housing, public education, health care and other benefits that urban citizens are entitled to.

21, the differences are very small and the two curves almost completely overlap. This assures us that labor migration experience exerts no significant influence on the timing when a rural woman enters her first marriage.

1.4 Theoretical Model

In this section, I develop a simple model that illustrates the underlying logic for how sex imbalance affects the daughter's non-agricultural labor supply in a household setting. In the context of rural China, non-farm employment is mostly associated with migration to urban areas in light of the relatively scarce non-agricultural job opportunities in rural villages. The objective of my model is to suggest potential mechanisms and to motivate my empirical work. Specifically, I aim to demonstrate two points. Firstly, young rural women with brothers are more likely to participate in migratory work in response to an increase in the local sex ratio. Secondly, as sex ratio rises, either the norm of son preference or marriage market pressure stimulates these women to work outside in order to support their brothers financially. Borrowing from Anderson and Eswaran (2009) and Heath and Tan (2018, 2019), I use a noncooperative framework that does not impose Pareto efficiency to model my story, although the main mechanisms would be similar in a collective setup (Browning and Chiappori, 1998).[6] This is in accordance with the recent literature showing that production or allocation decisions between household members are not necessarily efficient (Duflo and Udry, 2004; Robinson, 2012; Hoel, 2013).

I consider the decision problem of a household with both daughters and sons. Without loss of generality, I normalize the number of daughters to one. It needs to be emphasized that the number of sons is not specified as it is not a key ingredient of my model that affects the conclusion. My model consists of three players——the mother, the father, and the daughter——who care about their own utility derived from consumption and leisure,

[6] The model in Anderson and Eswaran (2009) aims to identify how earned and unearned income might determine the bargaining power of a woman relative to that of her husband. Heath and Tan (2018, 2019), in a similar vein, explore the effects of a woman's unearned income or her child's gender on her autonomy within a household.

and the sons' welfare. In other words, the household members display altruism towards the sons. The model can be extended to accommodate the situation where the parents also care about the daughter's welfare, as discussed in Appendix 1.B.1.2. For simplicity, I do not model the sons' decision making and regard them as pure recipients of family investment. The well-being of the sons is then assumed to be a household public good which is produced using parental time and monetary inputs and the financial contribution from the daughter.

I assume that in the noncooperative game the mother and the father specialize in parental investment in sons according to traditional gender roles: the mother is responsible for only time investment, while the father provides only monetary support. The separate spheres assumption is consistent with the tradition in many South Asian countries where women are relegated to home production and childcare while men devote themselves to income-raising activities. Lundberg and Pollak (1993) and Anderson and Eswaran (2009) also argue that even in a noncooperative scenario spouses operate in separate spheres in raising their children. Generalization allowing both spouses to make labor and monetary contributions shares result in a model with gender division of labor. I abstract from this possibility here as I assume below that time and money are perfect substitutes, following Anderson and Eswaran (2009), Heath and Tan (2018) and many others. Hence, the mother has three possible uses for her time: caring her sons, working in the labor market, and leisure. The father and the daughter each have two uses for their time: engaging in income-generating work, and leisure.

The above describes the general setup of my theory. The major innovation of my framework is that I incorporate the daughter's optimization problem into the classical separate spheres model. In the following analysis, the feature of son preference or marriage market pressure is introduced to formally link sex imbalance to the daughter's migratory work behavior. We can see from such a simplified model how the strength of son preference or marriage market competition affects the daughter's labor supply decision and even the labor force participation rate of young rural females. I next proceed to construct my baseline model deliberately stylized to explain first the functioning of the son preference channel, and then the functioning of the marriage market pressure channel.

1.4.1 The Mechanism of Son Preference

Assuming logarithmic utility, the objective function that the mother seeks to maximize can be written as[7]:

$$u_m(c_m, \pi, \ell_m) = \alpha_m^c \ln c_m + \alpha_m^\pi \rho_1 \ln \pi + \alpha_m^\ell \ln \ell_m$$

where c_m is her consumption of the market good, π is the well-being of her sons, and ℓ_m is her leisure. The mother allocates a unit of time to caring her sons h_m^1, outside work that brings an independent income h_m^2 and leisure ℓ_m, i.e., $h_m^1 + h_m^2 + \ell_m = 1$. To simplify the exposition, I follow Heath and Tan (2019) and assume that the labor supply decisions are made along the extensive margin: h_m^2 is a binary variable that takes 0 or H_m, where $H_m \in (0, 1)$ is exogenously given. A continuous version of the model is developed in Appendix 1.B.2. The parameter $\rho_1 > 0$ captures the degree of cultural preference towards sons and a larger ρ_1 implies that the mother pays greater attention to her sons' welfare. We can view the parameter ρ_1 as an increasing function of the local sex ratio. Since sex ratios in many cases mirror the intensity of son preference, a more male-biased sex ratio could be interpreted as reflecting the fact that a typical household attaches more weight to the sons' well-being. Besides, I impose restrictions on the other parameters of the mother's utility function such that $\alpha_m^c + \alpha_m^\pi + \alpha_m^\ell = 1$ and $0 \le \alpha_m^c, \alpha_m^\pi, \alpha_m^\ell \le 1$.

The utility function of the father takes a similar form:

$$u_f(c_f, \pi, \ell_f) = \alpha_f^c \ln c_f + \alpha_f^\pi \rho_1 \ln \pi + \alpha_f^\ell \ln \ell_f$$

where c_f is the amount of private good he consumes, π is the well-being of the sons, and ℓ_f is his leisure. I denote the amount of time the father spends working in the labor market as h_f, thus I have $\ell_f = 1 - h_f$. Similarly, h_f is assumed to be a binary choice between 0 and some exogenous $H_f \in (0, 1)$. I also normalize the parameters of the father's utility function such that $\alpha_f^c + \alpha_f^\pi + \alpha_f^\ell = 1$ and $0 \le \alpha_f^c, \alpha_f^\pi, \alpha_f^\ell \le 1$.

[7] This is a standard specification in the literature and adopted by Anderson and Eswaran (2009), Heath and Tan (2018) and many others.

An analogous utility function is posited for the daughter:

$$u_d\left(c_d, \pi, \ell_d\right) = \alpha_d^c \ln c_d + \alpha_d^\pi \rho_1 \ln \pi + \alpha_d^\ell \ln \ell_d$$

where her utility depends on her consumption of private good c_d, the well-being of her brothers π, and her leisure ℓ_d. Similar to the father, the daughter spends a unit of time on participation in market work h_d and leisure ℓ_d, i.e., $h_d + \ell_d = 1$. I again assume that the daughter chooses her labor supply through the extensive margin, i.e., h_d is either 0 or some exogenous $H_d \in (0, 1)$. The parameters of the daughter's utility function are also normalized to satisfy the restrictions that $\alpha_d^c + \alpha_d^\pi + \alpha_d^\ell = 1$ and $0 \leq \alpha_d^c, \alpha_d^\pi, \alpha_d^\ell \leq 1$.

The well-being of a son is determined by the mother's labor contribution h_m^1 and the monetary contributions, z_f and z_d, from his father and sister, respectively. To ensure analytical tractability, I make an additional simplifying assumption that the function, $g\left(h_m^1, z_f, z_d\right)$, for the sons' well-being is linear in the inputs

$$\pi = g\left(h_m^1, z_f, z_d\right) = \beta h_m^1 + z_f + z_d$$

where $\beta > 0$ and the sons' well-being equals to the family's total investment $I = \beta h_m^1 + z_f + z_d$. It is possible to construct an equivalent model where π is a nonlinear function of the inputs.

Apart from the financial contribution to her brother, the working daughter is also required to pay money to her parents. Both kinds of intra-household transfers are very common in developing countries, especially those in South Asia. For simplicity, I assume that the daughter pays a fraction of her earnings to the father.

Furthermore, I assume that both the parents and the daughter have unearned income. This assumption is made to guarantee positive consumption in the logarithmic utility case with binary labor supply decision, which is not necessary when the utility function is of a more general form or when labor supply is continuous.

The budget constraints are then given by

$$\begin{cases} p_m c_m \le E_m + w_m h_m^2, \\ z_f + p_f c_f \le E_f + w_f h_f + (1-\gamma)\, w_d h_d, \\ z_d + p_d c_d \le E_d + \gamma w_d h_d, \end{cases}$$

where p_m, p_f, p_d respectively denote the prices of the private goods that the mother, the father, and the daughter consume; w_m, w_f, w_d respectively denote the implicit wage rates the three players can earn in the labor market; E_m, E_f and E_d are their unearned endowments, respectively. The daughter retains a proportion, γ, of her total earned income and pays the remaining part of it, $(1-\gamma)\, w_d h_d$, to her father. The following proposition characterizes the effects of an increase in the degree of son preference on the Nash equilibrium.

Proposition 1.4.1. *Suppose the Nash equilibrium is fully interior. Then, in equilibrium, an increase in the degree of son preference (ρ_1): (1) increases the daughter's labor supply (h_d); (2) increases the father's labor supply (h_f); (3) decreases the mother's labor supply (h_m^2); (4) increases the family investment in the son (I); (5) increases the well-being of the son (π).*

The proof of the proposition is contained in Appendix 1.A.

An increase in the level of son preference, ceteris paribus, would raise the contribution of the sons' well-being, relative to consumption and leisure, to the family members' utilities. In this scenario, the marginal utility of the son's well-being increases and thus the three players would re-allocate their time to make its marginal gain the same in all uses. Specifically, to increase the sons' well-being, the father and the daughter would contribute a larger amount of money to them, and the mother would spend more time in caring them. This, in turn, induces the father and the daughter to engage more in outside work that earns independent income while reduces the mother's time allocated to the labor market.

On the other hand, in rich families, parents have sufficient resources to invest in the sons and the daughter has no need to work outside the home to support her brothers. Hence, we might expect a negative correlation between family wealth and the daughter's labor supply. In South Asia, most households accumulate their wealth through the father's earned income—thereby, the more the father earns, the less the daughter works. Similar logic applies when the daughter is endowed with higher unearned income. In the following proposition, I document the effects on the daughter's labor supply choice of the father's wage rate, the father's labor supply, the daughter's unearned income and the daughter's wage rate, respectively.

Proposition 1.4.2. *Suppose the Nash equilibrium is fully interior. Then, in equilibrium, I have: (1) an increase in the father's wage rate (w_f) decreases the daughter's labor supply (h_d); (2) an increase in the father's labor supply (h_f) decreases the daughter's labor supply (h_d); (3) an increase in the daughter's wage rate (w_d) increases the daughter's labor supply (h_d); (4) an increase in the daughter's unearned income (E_d) decreases the daughter's labor supply (h_d).*

An increase in the father's wage rate increases the likelihood that he works and thus his earned income. The father would increase his expenditure on private good, leading to a reduction in its marginal utility. He then responds to this by contributing more to the sons. This is because, in equilibrium, the marginal worth of the last dollar spent on private consumption must be equal to that spent on the sons' well-being. As the total contribution to the sons increases, the daughter gains more consumption on the public good——the sons' well-being——and more leisure[8]. The same logic applies to the case in which the father increases his labor supply.

1.4.2 The Mechanism of Marriage Market Pressure

The model described in the previous subsection yields the desired positive link between young rural female's migratory labor supply and local sex imbalance by relating sex ratios to the degree of son preference. A different and also more interesting explanation is that local sex ratios simply reflect the marriage market pressure faced by the households with sons and young rural women work outside their home villages in order to help share the burden

[8] The daughter spends more time on leisure since she must derive the same marginal utility from her consumption on public good and her consumption on leisure.

of financing their brothers' marriage. In a society with heavily male-biased sex ratios, the sons may experience a difficult time finding a suitable marriage partner due to the scarcity of young women. The plight of the sons would be alleviated if the parents invest more to increase their relative attractiveness through savings, house purchasing or other manners (Wei and Zhang, 2011a).

To model the mechanism of marriage market competition, I assume that the well-being of the sons is associated with their marriage prospects, which hinges on the family's total investment ($I = \beta h_m^1 + z_f + z_d$) and the severity of sex imbalance ρ_2 in the local marriage market. The function $g\left(h_m^1, z_f, z_d, \rho_2\right)$ for the sons' well-being is again assumed to be linear in the inputs:

$$\pi = g\left(h_m^1, z_f, z_d, \rho_2\right) = \beta h_m^1 + z_f + z_d - \rho_2 I_0 = I - \rho_2 I_0$$

where $\beta > 0$ and $I_0 > 0$ is the minimum level of investment that ensures the sons' marriage in a sex balanced society. Intuitively, the more the family invests in the sons, the more likely they are to succeed in finding spouses. For a high degree of sex imbalance, the household investment needs to exceed the minimum level I_0 by a large margin to maintain non-negative well-being for the sons. Here I assume $\beta + w_f + \gamma w_d + E_f + E_d - \rho_2 I_0 > 0$, where $(\beta + w_f + \gamma w_d + E_f + E_d)$ could be considered as the upper bound of the family's contribution to the sons. The upper bound is achieved when $h_m^1 = h_f = h_d = 1$ and $z_f = w_f h_f + E_f = w_f + E_f$, $z_d = \gamma w_d h_d + E_d = \gamma w_d + E_d$, which is a sufficient condition that avoids negative consumption for the daughter.

To highlight the workings of the marriage market pressure channel, I now assume that the preferences of the three players do not depend on the local sex ratio. Instead, the public good——the sons' well-being——is assumed to be decreasing in the degree of sex imbalance. These settings assist me in modeling the connection between marriage market competition and the labor supply of young rural women with brothers. I propose the following proposition that states the effects on the Nash equilibrium of an increase in the degree of sex imbalance in the marriage market.

Proposition 1.4.3. *Suppose the Nash equilibrium is fully interior. Then, in equilibrium, an increase in the degree of sex imbalance (ρ_2): (1) increases the daughter's labor supply (h_d); (2) increases the father's labor supply (h_f); (3) decreases the mother's labor supply (h_m^2); (4) increases the family investment in the sons (I); (5) decreases the well-being of the sons (π)*[9].

The proof of the proposition is contained in Appendix 1.A.

The marriage market pressure channel gives rise to similar comparative statics as the previous model. Both mechanisms generate a positive link between local sex ratios and the migratory labor supply of young rural women with brothers.

One could argue that the deficit of females improves the daughter's bargaining position in the marriage market, which may offset the daughter's desire to work outside. In Appendix 1.B.1, the theory is extended in two directions to incorporate the daughter's gain from the marriage market. First, I assume that a higher sex ratio increases household wealth through the future marital transfer from the groom's family. In another extension, I consider the environment where parents also invest in the daughter and where the daughter's well-being is positively correlated with the sex ratio imbalance. The two extensions yield no changes in the results as long as the average cost of having sons is larger than the average marital gain from the daughter[10].

1.4.3 The Relative Importance of the Two Channels

To focus on the relative importance of the two channels, I specialize the model to a setting with elements of both son preference and marriage market competition. The optimization

[9] Actually, there is no formal proof for this claim as the sons' well-being is a function of famliy members' of labor supply, which are discrete variables. Here I focus on how the change in marriage market pressure affects the change in the sons' well-being, holding other factors constant. A more rigorous derivation is provided in the continous case.

[10] This assumption is consistent with the reality in China. The expenditure of financing the sons' marriage mainly comes from the cost of purchasing a house, which is substantially larger than the bride price payment from the daughter's marriage.

problem for this case can be formulated as follows:

$$
\begin{aligned}
mother: \quad & \max_{c_m, h_m^1, h_m^2} \alpha_m^c \ln c_m + \alpha_m^\pi \rho_1 \ln \pi + \alpha_m^\ell \ln\left(1 - h_m^1 - h_m^2\right) \\
& s.t.\ \ h_m^2 \in \{0, H_m\}, \ 0 \leq h_m^1, h_m^2 \leq 1, \ h_m^1 + h_m^2 \leq 1, \ p_m c_m \leq E_m + w_m h_m^2 \\
father: \quad & \max_{c_f, z_f, h_f} \alpha_f^c \ln c_f + \alpha_f^\pi \rho_1 \ln \pi + \alpha_f^\ell \ln(1 - h_f) \\
& s.t.\ \ h_f \in \{0, H_f\}, \ 0 \leq h_f \leq 1, \ z_f + p_f c_f \leq E_f + w_f h_f + (1-\gamma) w_d h_d \\
daughter: \quad & \max_{c_d, z_d, h_d} \alpha_d^c \ln c_d + \alpha_d^\pi \rho_1 \ln \pi + \alpha_d^\ell \ln(1 - h_d) \\
& s.t.\ \ h_d \in \{0, H_d\}, \ 0 \leq h_d \leq 1, \ z_d + p_d c_d \leq E_d + \gamma w_d h_d
\end{aligned}
$$

where $\pi = I - \rho_2 I_0 = \beta h_m^1 + z_f + z_d - \rho_2 I_0$ is the well-being of the sons; the parameters ρ_1, ρ_2 capture the extent of son preference and the severity of marriage market pressure, respectively.

In equilibrium, the daughter chooses to work if and only if the following condition[11]

$$
\begin{aligned}
\Delta u_d(h_d) &= u_d(h_d = H_d) - u_d(h_d = 0) \\
&= \left(\alpha_d^c + \alpha_d^\pi \rho_1\right) \ln \frac{\beta\left(1 - h_m^2\right) + w_f h_f + w_d H_d + E_f + E_d - \rho_2 I_0}{\beta\left(1 - h_m^2\right) + w_f h_f + E_f + E_d - \rho_2 I_0} + \alpha_d^\ell \ln(1 - H_d) > 0
\end{aligned}
$$

is satisfied, or, equivalently, the implicit wage rate that the daughter can earn is sufficiently large:

$$
w_d > \left[(1 - H_d)^{-\alpha_d^\ell / \left(\alpha_d^c + \alpha_d^\pi \rho_1\right)} - 1\right] \cdot \frac{\beta\left(1 - h_m^2\right) + w_f h_f + E_f + E_d - \rho_2 I_0}{H_d} \equiv w_d^*
$$

To determine the fraction of daughters that participate in migratory work, I further consider the case where these daughters are heterogeneous in terms of the implicit wage rate w_d. Let w_d be characterized by the distribution function $F(w_d)$ with continuous marginal density $f(w_d) = F'(w_d)$. I assume that the density satisfies a set of restrictions: $F(0) = 0$, $F'(w_d) > 0$ for $w_d \in (0, +\infty)$, $\lim_{w_d \to 0} f(w_d) = 0$, and $\lim_{w_d \to +\infty} f(w_d) = 0$. Given

[11] This condition is a direct result from the proofs for Proposition 1.4.1 and Proposition 1.4.3, as shown in Appendix 1.A.

this assumption, the distribution of w_d thins out at each boundary, implying that all these daughters earn a positive income and the wage rate cannot be infinite. The proportion working N_d among these daughters can then be described by $N_d = 1 - F(w_d^*)$.

The elasticities of the daughters' labor force participation rate with respect to ρ_1 and ρ_2, which are denoted as ε_{ρ_1} and ε_{ρ_2}, are derived as follows

$$
\begin{aligned}
\varepsilon_{\rho_1} &= \frac{\partial N_d}{\partial \rho_1}\frac{\rho_1}{N_d} = \frac{\partial w_d^*}{\partial \rho_1}\frac{-\rho_1 f(w_d^*)}{1-F(w_d^*)} \\
&= (1-H_d)^{-\alpha_d^\ell/\left(\alpha_d^c+\alpha_d^\pi\rho_1\right)} \cdot \frac{\alpha_d^\ell\alpha_d^\pi \ln(1-H_d)}{\left(\alpha_d^c+\alpha_d^\pi\rho_1\right)^2} \cdot \frac{\beta\left(1-h_m^2\right)+w_f h_f+E_f+E_d-\rho_2 I_0}{H_d} \cdot \frac{-\rho_1 f(w_d^*)}{1-F(w_d^*)}, \\
\varepsilon_{\rho_2} &= \frac{\partial N_d}{\partial \rho_2}\frac{\rho_2}{N_d} = \frac{\partial w_d^*}{\partial \rho_2}\frac{-\rho_2 f(w_d^*)}{1-F(w_d^*)} \\
&= \left[(1-H_d)^{-\alpha_d^\ell/\left(\alpha_d^c+\alpha_d^\pi\rho_1\right)}-1\right] \cdot \frac{-I_0}{H_d} \cdot \frac{-\rho_2 f(w_d^*)}{1-F(w_d^*)}.
\end{aligned}
$$

It is easy to see that $\varepsilon_{\rho_1} > 0$ and $\varepsilon_{\rho_2} > 0$, suggesting that both channels could give rise to the positive correlation between local sex ratios and the labor migration rates of young rural women with brothers. I then define the ratio of ρ_2-elasticity to ρ_1-elasticity:

$$
\mathcal{R} = \frac{\varepsilon_{\rho_2}}{\varepsilon_{\rho_1}} = \frac{\left(\alpha_d^c+\alpha_d^\pi\rho_1\right)^2}{\alpha_d^\ell\alpha_d^\pi\rho_1 \ln(1-H_d)^{-1}} \cdot \frac{(1-H_d)^{\frac{-\alpha_d^\ell}{\left(\alpha_d^c+\alpha_d^\pi\rho_1\right)}}-1}{(1-H_d)^{\frac{-\alpha_d^\ell}{\left(\alpha_d^c+\alpha_d^\pi\rho_1\right)}}} \cdot \frac{\rho_2 I_0}{\beta\left(1-h_m^2\right)+w_f h_f+E_f+E_d-\rho_2 I_0}
$$

which measures the relative impacts of marriage market pressure and son preference on these daughters' labor supply.

Denote $\mathcal{Q} = \alpha_d^\ell \ln(1-H_d)^{-1} / \left(\alpha_d^c+\alpha_d^\pi\rho_1\right)$. I can rewrite $\mathcal{R}$ as

$$
\mathcal{R} = \frac{\alpha_d^c+\alpha_d^\pi\rho_1}{\alpha_d^\pi\rho_1} \cdot \frac{\exp(\mathcal{Q})-1}{\mathcal{Q}} \cdot \frac{1}{\exp(\mathcal{Q})} \cdot \frac{\rho_2 I_0}{\beta\left(1-h_m^2\right)+w_f h_f+E_f+E_d-\rho_2 I_0}
$$

where $\exp(\mathcal{Q}) \approx 1+\mathcal{Q}$. Recall that w_d^* is the critical value of w_d such that $\Delta u_d(h_d) = 0$, i.e.,

$$
\left(\alpha_d^c+\alpha_d^\pi\rho_1\right)\ln\frac{\beta\left(1-h_m^2\right)+w_f h_f+w_d^* H_d+E_f+E_d-\rho_2 I_0}{\beta\left(1-h_m^2\right)+w_f h_f+E_f+E_d-\rho_2 I_0} + \alpha_d^\ell \ln(1-H_d) = 0.
$$

Hence, the relative elasticity ratio $\mathcal{R}$ can be simplified to a product of two components

$$\mathcal{R} \approx \left(\frac{\alpha_d^c}{\alpha_d^\pi \rho_1} + 1\right) \cdot \left(\frac{1}{I^{\max} / (\rho_2 I_0) - 1}\right)$$

where $I^{\max} = [\beta(1 - h_m^2)] + [w_f h_f + E_f] + [w_d^* H_d + E_d]$, which is the maximum amount of family investment in the sons when the mother participates in the labor market. In the above expression, the first component is always larger than 1 and depends only on the relative weight that the daughter assigns to her consumption on private good compared to her male siblings' welfare. The denominator in the second component, $I^{\max}/(\rho_2 I_0) - 1$, measures the percentage by which the maximum level of household investment exceeds the minimum level of investment that guarantees nonnegative well-being of the sons. It is obvious to see that, as marriage market competition intensifies, chances are high that $I^{\max}/(\rho_2 I_0) - 1$ is smaller than 1 and thus $\mathcal{R}$ is larger than 1. This suggests that the daughter's labor supply is more sensitive to the marriage market pressure than the extent of son preference if the sex imbalance in the marriage market (ρ_2) is sufficiently severe. I summarize this result in the following proposition.

Proposition 1.4.4. *Suppose the Nash equilibrium is fully interior. Then, in equilibrium, the relative index $\mathcal{R}$ satisfies: (1) the degree of son preference (ρ_1) has little effect on the relative importance of the two channels; (2) if the sex imbalance in the marriage market (ρ_2) is sufficiently large, the daughter's labor supply elasticity with respect to marriage market pressure is higher than that to son preference.*

I next visualize the relative effects of the two channels by providing a numerical illustration of how the relative ratio $\mathcal{R}$ evolves as the parameters ρ_1, ρ_2 change[12]. In Figure 1.8, I let one of the parameters ρ_1, ρ_2 vary while keeping the other fixed. Figure 1.9 provides a contour plot of $\mathcal{R}$ connecting different values of ρ_1 and ρ_2. It can be seen from both Figure 1.8 and Figure 1.9 that, under most scenarios, $\mathcal{R}$ is larger than 1. This indicates that the

[12]In this example, the parameter values are $\alpha_d^c = 0.5$, $\alpha_d^\pi = 0.25$, $\alpha_d^\ell = 0.25$, $H_d = 0.6$, $\frac{I^{\max}}{I_0} = \frac{\beta(1-h_m^2)+w_f h_f + E_f + E_d}{I_0} = 2$. I also use alternative sets of parameters in Appendix Figure 1.A1, which exhibits similar patterns.

mechanism of marriage market pressure seems to play a more influential role in shaping the labor migration behavior of young rural females who have brothers.

1.5 Data and Variables

1.5.1 Source of Household-Level Data

My empirical analysis uses data from the Longitudinal Survey on Rural-Urban Migration in China (RUMiC). This project was established to facilitate the understanding of the overall impacts and patterns of migration in China, and was initiated by a group of researchers at the Australian National University, Beijing Normal University and the Institute for the Study of Labor (IZA). First launched in 2008 (Wave 1), the RUMiC survey covers the principal sending and receiving regions of rural-to-urban migration. Follow-up Waves 2 to 6, which involve the same households, were conducted annually between 2009 and 2013. Each wave is composed of three independent surveys: the Urban Household Survey (UHS), the Rural Household Survey (RHS) and the Migrant Household Survey (MHS). This paper focuses primarily on the first and second waves of the RHS[13], which collects data on rural households through face-to-face interview in villages across nine provinces[14].

The RHS is conducted at both the household and community level. To ensure the quality and representativeness of the data, the households surveyed are randomly selected based on a three-stage stratified and systematic sampling procedure. This design is also used in the Annual Rural Household Survey implemented by the China's NBS. For each selected family, the survey provides comprehensive information on the demographic and socioeconomic characteristics of all family members, including the household head and members who are officially registered or who have been living for over 6 months in the household. More importantly, for my purpose, it has detailed information on personal migration history as well as family relationship that helps identify the sibling structure within each household. For the sampled

[13] Waves 3-6 of the survey data have not been published.

[14] The provinces are: Shanghai, Jiangsu, Zhejiang, Hubei, Sichuan, Guangdong, Henan, Anhui and Sichuan.

villages, the community-level dataset contains variables on local economic conditions, public services, agricultural production, and land management, etc.

My sample is restricted to unmarried rural females who are aged above 16 and below 50. I focus on this subsample for two reasons. For one thing, firms in China are not allowed to employ workers aged below 16 who are supposed to be attending school for the 9-year compulsory education. For another, in most cases, a married daughter is no longer regarded as a member of her original family, and barely participates in the household decision making. I also drop women who are still at school, disabled or retired.

1.5.2 Main Outcome and Control Variables

My main outcome variable of interest is the migration status of an unmarried rural woman. To create my measure of migration status, I mainly rely on three questions in the survey. Every member in the household is required to answer each of these questions. The first question is: "How many months have you been living away from the local countryside this year?" The second is: "If you have been living outside the local countryside for more than 3 months this year, where did you live?" Finally, the third question is: "What is the main reason you have been living outside the local countryside for more than 3 months this year?" Based on these questions, I define the migration status as a binary variable that takes on the value one if the rural woman has been living in urban areas for over 3 months this year for work or business, and zero otherwise. I also examine the migration experience of an unmarried rural woman, which is captured by a dummy variable for whether the woman has ever migrated for nonagricultural work.

The empirical analysis takes into account a set of standard personal characteristics of the rural woman that could potentially affect her migration behavior, including years of education, age, birth order, ethnicity and health condition. The ethnicity dummy is set to one for rural women who are Han Chinese, and to zero for those who are minorities. The health information comes from a survey question that asks the respondents to evaluate their current state of health compared to people of the same age on a scale from 1 (*excellent*) to 5 (*very poor*). I reverse the response scale to indicate the respondent's health condition: the larger the number, the healthier the respondent is. I also control for the health status of the woman's father and mother, family size as well as the wealth level of the household. I define the family wealth as per capita market present value of self-owned housing at the end of the year, which is measured in ten thousands of yuan.

The summary statistics for my sample are reported in Table 2.1. Overall, in the whole sample, 57.8% of unmarried rural women have been working outside the home village in the survey year, and 68.6% of them report ever having labor migration experience. On average, the sampled women have about 9 years of schooling, and are around 21 years old. The fraction of Han Chinese is as high as 99.1%. The mean self-rated health score of the rural women is 4.28, and those for the father and the mother are 3.92 and 3.78, respectively. The average per capita family wealth is 15,440 yuan.

I also present the summary statistics broken down by rural women who have brothers or not. As shown in Table 2.1, rural women with brothers are more likely to participate in migratory work than those who have no brothers. Among rural women with brothers, 62.4% of them report having migrated for work in the current year, and 71.9% report that they have ever worked in urban areas. The corresponding figures for rural women without brothers are 50.8% and 63.8%, respectively. In addition, I find that the per capita wealth level is about 56% higher for rural women with no brothers, which might be a result of smaller family size. The differences are economically very small for each of the other characteristics between the two groups of rural women.

Finally, I perform the Kolmolgorov-Smirnov test to compare the distributions of these variables in the two samples of rural women. The corresponding test statistic and p-values are summarized in the last two columns. As can be seen, I find statistically significant disparities in the distributions of migration behavior, educational outcomes, per capita family wealth, family size and birth order between the two groups of rural women; while I cannot reject the null that the other variables are identically distributed in the two samples at the 1% significance level.

1.5.3 Local Sex Ratios from Census Data

For my main analysis, I focus on the effects of the local sex ratio on unmarried rural women's labor migration behavior. I calculate the local sex ratio as the number of males per female for certain age cohorts in the woman's county of birth using the 1% sample of the 1990 Population Census. To reflect the marriage market pressure faced by the woman's family, I mainly consider the sex ratio for individuals aged between 16 and 20 for two reasons. First, as discussed in Section 3, households could form expectations about the marriage market prospects in the near future by observing the sex ratio for this premarital age group. Second, this sex ratio is also applied to families with sons who are at the prime marriageable age since men usually marry relatively young women in China. I also make use of sex ratios for older cohorts as sensitivity and placebo tests.

The key strength of utilizing the 1990 Population Census is that it largely avoids the migration bias in the calculation of local sex ratios. Prior to 1990, migration is less usual in China. The central government has maintained stringent controls over internal migration until the 1990s when a market economy was formally established. The migration rate in the whole population is only about 3%, which should not substantially bias the local sex ratios.

1.5.4 Other County-Level Controls

Rural women's migration decision may also be affected by local economic conditions which could be related to local sex ratios. To account for such possibility, I include several county-level variables that capture the economic and financial development as well as non-agricultural employment opportunities of the local areas. I obtain the county-level data from China statistical year book for regional economy and China county statistical year book. In particular, I control for per capita GDP, per capita disposable income of rural households, the average wage in the urban sector, saving deposits by residents, loans in financial institutions and per capita number of firms.

1.6 Conceptual Framework

In this section, I present a *treatment-in-treatment* (TIT) framework for identifying the difference in labor migration choice induced by sex imbalance between rural women with brothers and those without brothers. To fix ideas, I consider a causal effect model with a binary outcome variable and an interaction of two treatments—one is continuous and the other is discrete. My application is to assess how the causal effect of the local sex ratio on rural women's labor migration outcome differs by the male sibling structure. For concreteness, I denote the migration status of rural woman i by $Y_i \in \{0, 1\}$, the county-level sex ratio by sr, and the number of brothers rural woman i has by $D_i \in \{0, 1, \cdots, D_{\max}\}$, where $D_{\max}$ is the maximum number of brothers I observe in the sample. The county-specific sex ratio sr is a continuous treatment whereas the individual-specific male sibling size D_i is a discrete ordered treatment. My analysis is flexible to embrace the setting where D_i is a binary indicator for whether the rural woman has brothers or not. Let $\mathbf{X}_i$ be the conditioning covariates, and u_i be the unobserved random factors. The rural woman's migration choice is determined by the local sex ratio sr, her male sibling structure D_i, and other observable characteristics $\mathbf{X}_i$ and unobservables u_i, i.e.,

$$Y_i = Y_i\left(sr, D_i, \mathbf{X}_i, u_i\right).$$

Fixing D_i, $\mathbf{X}_i$ and u_i, the causal effect of the local sex ratio on the rural woman's propensity to migrate is then defined by

$$\nabla_{sr} Y_i \equiv \nabla_{sr} Y_i\left(sr, D_i, \mathbf{X}_i, u_i\right).$$

The main interest of my paper is to explore the variation in $\nabla_{sr} Y_i$ across different values of D_i, which can be interpreted as the causal effect of the interaction of the two treatments on the rural female's migration status. To do so, my identification strategy proceeds in two steps. First, conditional on sr and $\mathbf{X}_i$, I identify the average treatment effect of D_i on Y_i denoted by $\tau\left(sr, \mathbf{X}_i\right)$. Second, I evaluate the average marginal effect of changes in local sex ratio on $\tau\left(sr, \mathbf{X}_i\right)$, which is defined as $\nabla_{sr}\tau\left(sr, \mathbf{X}_i\right) = \partial\tau\left(sr, \mathbf{X}_i\right)/\partial sr$. In principle, the quantity $\nabla_{sr}\tau\left(sr,\mathbf{X}_i\right)$ also measures how the marginal effect of sex imbalance on rural women's migration decision varies by the number of male siblings under some weak conditions. I formalize the assumptions that are needed to ensure the validity of the suggested procedure as follows.

Assumption 1.6.1. (Conditional independence assumption) *Conditional on the woman's observable characteristics $\left(D_i,\mathbf{X}_i\right)$, the county-specific sex ratio sr is statistically independent of the individual-specific random components u_i, i.e., $f\left(u_i|\, sr, D_i, \mathbf{X}_i\right) = f\left(u_i|\, D_i, \mathbf{X}_i\right)$.*

This assumption is acceptable as I can control for a wide array of personal and county-level characteristics. Moreover, the local sex ratio is considered exogenous in the context of China as discussed later in the next section[15].

The above assumption provides general conditions under which the average causal effect of interest is identified, as justified by the proposition below.

Proposition 1.6.1. *Suppose Assumption 1.6.1 holds. Conditional on the observed covariates $\mathbf{X}_i$, denote the average causal effect of interest as $\psi_{ace}\left(\mathbf{X}_i\right)$, where*

$$\psi_{ace}\left(\mathbf{X}_i\right) = \mathbb{E}\left[\nabla_{sr}\tau_i\left(sr,\mathbf{X}_i\right)|\, sr, D_i, \mathbf{X}_i\right] = \int_{\mathbb{R}_u} \nabla_{sr}\tau_i\left(sr,\mathbf{X}_i\right) f\left(u_i|\, sr, D_i, \mathbf{X}_i\right) du_i,$$

and $\tau_i\left(sr,\mathbf{X}_i\right)$ is the individual treatment effect of D_i on Y_i. Then, $\psi_{ace}\left(\mathbf{X}_i\right)$ can be identified as the partial derivate of the average treatment effect $\tau\left(sr,\mathbf{X}_i\right)$ with respect to sr

$$\psi_{ace}\left(\mathbf{X}_i\right) = \nabla_{sr}\mathbb{E}\left[\tau_i\left(sr,\mathbf{X}_i\right)|\, sr, D_i, \mathbf{X}_i\right] = \nabla_{sr}\tau\left(sr,\mathbf{X}_i\right).$$

The proposition implies that $\psi_{ace}\left(\mathbf{X}_i\right)$ can be recovered from the partial derivative of $\tau\left(sr,\mathbf{X}_i\right)$ with respect to the sex ratio. Accordingly, in order to identify $\psi_{ace}\left(\mathbf{X}_i\right)$, I only need to examine the behavior of $\tau\left(sr,\mathbf{X}_i\right)$.

Before moving forward, let me introduce some notation. First, I rewrite the migration variable in the language of potential outcomes. For a certain local sex ratio sr, I only observe

[15] I also employ an instrumental variable strategy to further determine the causal relationship between the local sex ratio and rural women's labor migration outcome in a robustness check.

one migration status $Y_i^{D_i}(sr, \mathbf{X}_i)$ for each rural female. The observed migration outcome can be expressed as[16]

$$Y_i(sr, \mathbf{X}_i) = \sum_{j=0}^{D_{\max}} \mathbf{1}\{D_i = j\} \cdot Y_i^j(sr, \mathbf{X}_i)$$

where $\mathbf{1}\{\cdot\}$ is the indicator function. In what follows, I separately discuss the cases of exogenous D_i and endogenous D_i. The details of the proofs of the relevant propositions are provided in Appendix 1.C.

1.6.1 Identification with Exogenous Treatment

According to Proposition 1.6.1, identification of the average causal effect of interest, $\psi_{ace}(\mathbf{X}_i)$, reduces to recovering $\tau(sr, \mathbf{X}_i)$. I start the analysis by formulating the estimands of the treatment effect of D_i on Y_i that are identified when the treatment variable D_i is regarded as exogenous. Before I discuss and describe the identification results, I first make the following regular assumptions on D_i of the treatment evaluation framework (Rubin, 1978; Rosenbaum and Rubin, 1983).

Assumption 1.6.2. (Ignorability) $\quad Y_i^j \perp\!\!\!\perp D_i \mid \mathbf{X}_i \quad \forall j \in \{0, 1, \cdots, D_{\max}\}$

Assumption 1.6.3. (Overlap) $\quad 0 < \Pr[D_i = j | \mathbf{X}_i] < 1 \quad \forall j \in \{0, 1, \cdots, D_{\max}\}$

These assumptions can be used to interpret differences in average migration outcomes between rural women with different number of male siblings. Let $p^j(\mathbf{X}_i) = \Pr[D_i = j | \mathbf{X}_i]$ denote the conditional probability of having j brothers. The following proposition shows that identification of the unconditional average causal response between rural women with j brothers and those with k brothers can be achieved by using inverse propensity score weighting (Busso et al., 2009).

[16] I follow the conventional assumption in the literature that the potential outcomes of any individual are not affected by the assignment of treatments to the other individuals, which is known as the stable unit treatment value assumption (SUTVA).

Proposition 1.6.2. *For a given level of local sex imbalance sr, the average treatment effect between $D_i = j$ and $D_i = k$ satisfies*

$$\begin{aligned}\tau_{ate}^{j,k}(sr, \mathbf{X}_i) &= \mathbb{E}\left[Y_i^j(sr, \mathbf{X}_i) - Y_i^k(sr, \mathbf{X}_i)\middle| \mathbf{X}_i\right] \\ &= \mathbb{E}\left[\left(\frac{\mathbf{1}\{D_i = j\}}{p^j(\mathbf{X}_i)} - \frac{\mathbf{1}\{D_i = k\}}{p^k(\mathbf{X}_i)}\right) Y_i(sr, \mathbf{X}_i)\middle| \mathbf{X}_i\right]\end{aligned}$$

for all $j, k \in \{0, 1, \cdots, D_{\max}\}$.

It is clear from Proposition 1.6.2 that I identify different treatment effects with different pairs of (j, k), either at the extensive margin or the intensive margin, as depicted by Figure 1.10. To recover the overall impact of having brothers, I define a weighted average treatment effect

$$\tau_{ate}(sr, \mathbf{X}_i) = \sum_{j=1}^{D_{\max}} w^j(\mathbf{X}_i)\, \tau_{ate}^{j,0}(sr, \mathbf{X}_i)$$

where $w^j(\mathbf{X}_i) = p^j(\mathbf{X}_i) / \sum_{l=1}^{D_{\max}} p^l(\mathbf{X}_i) = \Pr[D_i = j | \mathbf{X}_i, D_i \neq 0]$ and $\sum_{l=1}^{D_{\max}} p^l(\mathbf{X}_i) = 1 - p^0(\mathbf{X}_i)$. Notice that $\tau_{ate}(sr, \mathbf{X}_i)$ is a weighted average of the treatment effects at the extensive margin, i.e., the overall effect of having brothers.

The next proposition provides a propensity score approach to establish identification, and it also demonstrates that the weighted average treatment effect is essentially the difference between weighted average outcomes of the treated groups and the average outcome of the control group.

Proposition 1.6.3. *For a given level of sex imbalance sr, the weighted average treatment effect satisfies*

$$\tau_{ate}(sr, \mathbf{X}_i) = \sum_{j=1}^{D_{\max}} w^j(\mathbf{X}_i)\, \tau_{ate}^{j,0}(sr, \mathbf{X}_i) = \mathbb{E}\left[\sum_{j=1}^{D_{\max}} w^j(\mathbf{X}_i)\, Y_i^j(sr, \mathbf{X}_i) - Y_i^0(sr, \mathbf{X}_i)\middle| \mathbf{X}_i\right]$$

and

$$\tau_{ate}(sr, \mathbf{X}_i) = \mathbb{E}\left[\frac{\left(p^0(\mathbf{X}_i) - \mathbf{1}\{D_i = 0\}\right) Y_i(sr, \mathbf{X}_i)}{p^0(\mathbf{X}_i)\left(1 - p^0(\mathbf{X}_i)\right)}\middle| \mathbf{X}_i\right].$$

1.6.2 Identification with Endogenous Treatment

While I can control for a series of possible confounding factors, there could still be some unobserved household characteristics that are simultaneously associated with both the number of brothers a rural woman has and her labor migration behavior. To capture the exogenous variation in the number of brothers, I adopt two sibling variants from the last generation, i.e., the number of brothers that the father and the mother ever have. Since children tend to replicate the family composition of the parents, I posit that the rural woman is more likely to have brothers if her parents were growing up in a family with a larger fraction of male siblings[17]. Such intergenerational transmission of fertility is well documented in the literature (e.g., Booth and Kee, 2009; Murphy, 2013), reflecting not only the importance of early-life experience on later-life outcomes but also the heritability of sex ratio gene from parents to offspring (Gellatly, 2009; Kohler et al., 1999).

I claim that my instruments are as good as randomly assigned when I control for the total number of siblings that the parents ever have, for the following reasons. First, the parents in my sample were born before the implementation of the One Child Policy (OCP). As discussed in the paper, it was only after China enforced the stringent birth control policy that sex selective practices and sex ratio distortions became increasingly prevalent. In addition, ultrasound technology was first introduced in the market in 1980s after the OCP. It is almost impossible for a rural woman who was pregnant before 1980 to perform prenatal sex selection. In this scenario, given the total number of children ever born, the gender of the children is randomly determined by nature (Zhou, 2014). Furthermore, in the Mao era (1949-1978), the Chinese government made great endeavor to promote gender equality, as manifested by the well-known slogan "Women hold up half the sky". The improved status of women in this period should lead to diminished intensity of son preference and also less gender selection behavior. Finally, I regress my instruments on a series of personal and

[17]It should also be noted that my instruments affect only parental preference over family composition rather than preference towards children of a certain gender. One's perception of son preference is often inherited from the parents through the socialization process. Since the fractions of brothers that the rural woman's parents ever have are randomly determined, they should not capture the family culture of gender preference.

background characteristics of the rural women but find almost no significant relation. This suggests that rural women assigned with different instrument values are comparable at least in terms of observed characteristics. Therefore, it seems safe to assume that once the size of the parents' siblings is controlled for, the number of their brothers is exogenous.

Let Z_i^m and Z_i^f denote the two brother variants from the parents' generation, where the superscript m is for mother and f is for father. As argued by Angrist et al. (2000), in the case with discrete instruments, what matters is not the number of instruments but the number of distinct values of the instrument vector. Without loss of generality, I order the instrument values by their sum and assume that the number of the father's brothers has a more crucial effect than that of the mother's. Similar to von Hinke et al. (2016), I map the instrument values $\left(Z_i^m, Z_i^f\right)$ onto the support $\{z\,|z \in \mathbb{R}^+,\, 1 \leq z \leq Z_{\max}\}$, which generates the corresponding instrument Z_i I need. For example, suppose the maximum number of brothers observed is 3, then Z_i takes 16 possible values as presented in the following table.

Number of brothers $Z_i^m + Z_i^f$	Instrument values $\left(Z_i^m, Z_i^f\right)$	Corresponding instrument Z_i
0	(0,0)	1
1	(0,1), (1,0)	2, 3
2	(0,2), (1,1), (2,0)	4, 5, 6
3	(0,3), (1,2), (2,1), (3,0)	7, 8, 9, 10
4	(1,3), (2,2), (3,1)	11, 12, 13
5	(2,3), (3,2)	14, 15
6	(3,3)	16

The observed treatment D_i now can be written as

$$D_i = \sum_{z=0}^{Z_{\max}} \mathbf{1}\left\{Z_i = z\right\} \cdot D_i^z$$

where D_i^z is the potential treatment if $Z_i = z$. The standard assumptions for instrument validity are given as follows.

Assumption 1.6.4. (Independence) $\left\{Y_i^j,\, D_i^z\right\} \perp\!\!\!\perp Z_i \mid \mathbf{X}_i \quad \forall\, j \in \{0, 1, \cdots, D_{\max}\}, z \in$

$\{0, 1, \cdots, Z_{\max}\}$

Assumption 1.6.5. (Exclusion) $\mathbb{E}\left(Y_i | \mathbf{X}_i, D_i, Z_i\right) = \mathbb{E}\left(Y_i | \mathbf{X}_i, D_i\right)$

Assumption 1.6.6. (Nontrivial instruments) $\mathbb{E}\left(D_i | \mathbf{X}_i, Z_i\right) \neq \mathbb{E}\left(D_i | \mathbf{X}_i\right)$

Assumption 1.6.7. (Monotonicity) $\Pr\left[D_i^z \geq D_i^{z'} \middle| \mathbf{X}_i\right] = 1 \quad \forall\, z \geq z'$

The independence assumption states that given the conditioning covariates $\mathbf{X}_i$, the probability distribution of female labor migration over the range of possible numbers of brothers in the two generations is independent of the realized number of brothers that the parents ever have. The exclusion restriction highlights that the outcome function $Y_i^j(z)$ does not depend on the instrument and can be simply written as Y_i^j. The instrument can only affects the outcome through affecting the treatment. The instrument in a nontrivial fashion suggests that the expected treatment given z and covariates differs from that with z' and the same covariates. Hence, the instrument has an impact on the exposure to treatment. The monotonicity assumption (Angrist et al., 2000) is used to rule out defiers in the population. For every individual i, an increase in the value of the instrument from z to z' will not reduce the treatment intensity holding covariates $\mathbf{X}_i$ constant. In my discussion, it amounts to requiring that the number of brothers a rural female has is weakly increasing in the number of brothers her parents ever have.

Define the local average treatment effect as the ratio of the difference in expected migration outcomes at two values of the instrument to the difference in expected male sibling size at the same two values of the instrument, i.e.,

$$\tau_{late}^{z,z'}(sr, \mathbf{X}_i) = \frac{\mathbb{E}\left[Y_i(sr) | Z_i = z, \mathbf{X}_i\right] - \mathbb{E}\left[Y_i(sr) | Z_i = z', \mathbf{X}_i\right]}{\mathbb{E}\left[D_i | Z_i = z, \mathbf{X}_i\right] - \mathbb{E}\left[D_i | Z_i = z', \mathbf{X}_i\right]}.$$

Under the above assumptions, the local average treatment effect identifies a weighted average of the causal effects of having an additional brother on rural women's migration status for different groups of compliers (see Angrist et al., 2000):

$$\tau_{late}^{z,z'}(sr, \mathbf{X}_i) = \sum_{j=1}^{D_{\max}} \omega_j^{z,z'} \mathbb{E}\left[Y_i^j(sr) - Y_i^{j-1}(sr) \middle| \underbrace{D_i^{z'} < j \leq D_i^z}_{\text{Compliers of } j}, \mathbf{X}_i\right]$$

for all $z \geq z'$ and $z, z' \in \{0, 1, \cdots, Z_{\max}\}$, where

$$\omega_j^{z,z'} = \frac{\Pr\left[D_i^{z'} < j \leq D_i^z \middle| \mathbf{X}_i\right]}{\sum_{j=1}^{D_{\max}} \Pr\left[D_i^{z'} < j \leq D_i^z \middle| \mathbf{X}_i\right]}.$$

Intuitively, it can also be viewed as recovering a weighted sum of the treatment effect of having more brothers for rural women who would have no brothers if assigned a smaller instrument value, and the treatment effect for those who would counterfactually have fewer brothers:

$$\begin{aligned}\tau_{late}^{z,z'}(sr, \mathbf{X}_i) = \omega_{\text{exten}}^{z,z'} \cdot \underbrace{\mathbb{E}\left[Y_i^{D_i^z}(sr) - Y_i^{D_i^{z'}}(sr) \middle| D_i^z > D_i^{z'} = 0, \mathbf{X}_i\right]}_{\text{Extensive margin}} \\ + \omega_{\text{inten}}^{z,z'} \cdot \underbrace{\mathbb{E}\left[Y_i^{D_i^z}(sr) - Y_i^{D_i^{z'}}(sr) \middle| D_i^z > D_i^{z'} > 0, \mathbf{X}_i\right]}_{\text{Intensive margin}}\end{aligned}$$

where[18]

$$\omega_{\text{exten}}^{z,z'} = \frac{\Pr\left[D_i^z > D_i^{z'} = 0 \middle| \mathbf{X}_i\right]}{\sum_{j=1}^{D_{\max}} \Pr\left[D_i^{z'} < j \leq D_i^z \middle| \mathbf{X}_i\right]}, \quad \omega_{\text{inten}}^{z,z'} = \frac{\Pr\left[D_i^z > D_i^{z'} > 0 \middle| \mathbf{X}_i\right]}{\sum_{j=1}^{D_{\max}} \Pr\left[D_i^{z'} < j \leq D_i^z \middle| \mathbf{X}_i\right]}.$$

This interpretation is built on the idea in Rose and Shem-Tov (2018) with suitable modifications.

The local average treatment effect established above is not unique in my setup where Z_i is multivalued. Different pairs of instrument values may produce different causal parameters. I now consider an estimand that weights the causal parameters based on all pairs of adjacent instrument values. Formally, I define a weighted average treatment effect as the ratio of the covariance of the migration outcome and some function $f(\cdot)$ of the instrument to the

[18]By construction, the weights $\omega_{\text{exten}}^{z,z'}$ and $\omega_{\text{inten}}^{z,z'}$ measure the relative importance of the extensive and intensive margin effects of having brothers on $\tau_{late}^{z,z'}(sr, \mathbf{X}_i)$, which can be computed using the inverse probability weighting method (Robins et al., 1994; Hirano et al., 2003; Abadie and Cattaneo, 2018).

covariance of the treatment and the same function of the instrument,

$$\tau_{wate}(sr, \mathbf{X}_i) = \frac{Cov\left[Y_i(sr), f(Z_i) | \mathbf{X}_i\right]}{Cov\left[D_i, f(Z_i) | \mathbf{X}_i\right]}.$$

Here the function $f(\cdot)$ is often be attained from a first stage regression of the treatment on the instrument. As in Angrist et al. (2000) and Angrist and Imbens (2009), it will be shown that $\tau_{wate}(sr, \mathbf{X}_i)$ is a weighted average of $\tau_{late}^{z,z-1}(sr, \mathbf{X}_i)$ where the weights are proportional to the first stage impact:

$$\tau_{wate}(sr, \mathbf{X}_i) = \sum_{z=1}^{Z_{\max}} \tilde{\omega}^z \tau_{late}^{z,z-1}(sr, \mathbf{X}_i)$$

where

$$\tilde{\omega}^z = \frac{\sum_{j=1}^{D_{\max}} \Pr\left[D_i^{z-1} < j \leq D_i^z \middle| \mathbf{X}_i\right] \cdot \sum_{k=z}^{Z_{\max}} \Pr\left[Z_i = k | \mathbf{X}_i\right]\left(f(k) - \mathbb{E}\left[f(k) | \mathbf{X}_i\right]\right)}{\sum_{z=1}^{Z_{\max}} \sum_{j=1}^{D_{\max}} \Pr\left[D_i^{z-1} < j \leq D_i^z \middle| \mathbf{X}_i\right] \cdot \sum_{k=z}^{Z_{\max}} \Pr\left[Z_i = k | \mathbf{X}_i\right]\left(f(k) - \mathbb{E}\left[f(k) | \mathbf{X}_i\right]\right)}.$$

Analogously, one can decompose $\tau_{wate}(sr, \mathbf{X}_i)$ as a weighted sum of extensive and intensive margin impacts of having more brothers[19]:

$$\begin{aligned}\tau_{wate}(sr, \mathbf{X}_i) = & \underbrace{\sum_{z=1}^{Z_{\max}} \tilde{\omega}_{\text{exten}}^z \cdot \mathbb{E}\left[Y_i^{D_i^z}(sr) - Y_i^{D_i^{z-1}}(sr) \middle| D_i^z > D_i^{z-1} = 0, \mathbf{X}_i\right]}_{\text{Linear combination of extensive margin effects}} \\ & + \underbrace{\sum_{z=1}^{Z_{\max}} \tilde{\omega}_{\text{inten}}^z \cdot \mathbb{E}\left[Y_i^{D_i^z}(sr) - Y_i^{D_i^{z-1}}(sr) \middle| D_i^z > D_i^{z-1} > 0, \mathbf{X}_i\right]}_{\text{Linear combination of intensive margin effects}}\end{aligned}$$

where $\tilde{\omega}_{\text{exten}}^z = \tilde{\omega}^z \omega_{\text{exten}}^{z,z-1}$, $\tilde{\omega}_{\text{inten}}^z = \tilde{\omega}^z \omega_{\text{inten}}^{z,z-1}$ and $\sum_{z=1}^{Z_{\max}} \left(\tilde{\omega}_{\text{exten}}^z + \tilde{\omega}_{\text{inten}}^z\right) = 1$.

[19]We can similarly estimate the weights using inverse probability weighting approach as previously explained.

1.6.3 Treatment Effect Variation Interpretation

As previously analyzed, the key step in the identification of the $\psi_{ace}(\mathbf{X}_i)$ is recovering $\tau(sr, \mathbf{X}_i)$. Essentially, the average causal effect of interest $\psi_{ace}(\mathbf{X}_i)$ can be interpreted in the treatment effect variation framework. That is, we can view $\psi_{ace}(\mathbf{X}_i)$ as how the treatment effect of having brothers varies by the sex ratio.

To see this, consider the individual treatment effect of having j brothers instead of having k brothers $\tau_i^{j,k}(sr, \mathbf{X}_i)$. Following the spirit of existing literature (Heckman et al., 1997; Djebbari and Smith, 2008; Ding et al., 2019), $\tau_i^{j,k}(sr, \mathbf{X}_i)$ can be decomposed via

$$\tau_i^{j,k}(sr, \mathbf{X}_i) = \psi^{j,k} \cdot sr_i + \mathbf{X}_i' \gamma^{j,k} + \nu_i^{j,k}$$

where $\psi^{j,k} \cdot sr_i$ is known as the systematic treatment effect variation explained by local sex ratio, and $\nu_i^{j,k}$ is the idiosyncratic treatment effect variation. The vector of parameters $\left(\psi^{j,k}, \gamma^{j,k\prime}\right)$ can be estimated using the following randomization-based unbiased estimator

$$\begin{pmatrix} \hat{\psi}^{j,k} \\ \hat{\gamma}^{j,k} \end{pmatrix} = \boldsymbol{Q}_{sr,\mathbf{X}}^{-1} \left(\frac{1}{n_j} \sum_{i=1}^{n_{j,k}} \mathbf{1}\{D_i = j\} Y_i \mathbf{M}_i - \frac{1}{n_k} \sum_{i=1}^{n_{j,k}} \mathbf{1}\{D_i = k\} Y_i \mathbf{M}_i \right)$$

with covariance matrix from the finite population inference

$$Cov \begin{pmatrix} \hat{\psi}^{j,k} \\ \hat{\gamma}^{j,k} \end{pmatrix} = \boldsymbol{Q}_{sr,\mathbf{X}}^{-1} \left[\underbrace{\frac{\mathcal{S}\left\{Y_i^j \ \mathbf{M}_i\right\}}{n_j} + \frac{\mathcal{S}\left\{Y_i^k \ \mathbf{M}_i\right\}}{n_k}}_{\text{Conservative covariance matrix}} - \underbrace{\frac{\mathcal{S}\left\{\left(Y_i^j - Y_i^k\right) \mathbf{M}_i\right\}}{n_{j,k}}}_{\text{Unidentifiable component}} \right] \boldsymbol{Q}_{sr,\mathbf{X}}^{-1}$$

where $\boldsymbol{Q}_{sr,\mathbf{X}}^{-1} = \frac{1}{n_{j,k}} \sum_{i=1}^{n_{j,k}} \mathbf{M}_i \mathbf{M}_i'$, $\mathbf{M}_i' = (sr_i, \mathbf{X}_i')$, $n_{j,k} = n_j + n_k$ is the number of observations in the two categories, and $\mathcal{S}\{\mathbf{V}_i\} = \frac{1}{n-1} \sum_{i=1}^{n} \left(\mathbf{V}_i - \bar{\mathbf{V}}\right)\left(\mathbf{V}_i - \bar{\mathbf{V}}\right)'$ is the finite population covariance function of vector $\mathbf{V}_i$ that could be estimated by sample analog. The last term in the bracket is unidentifiable but vanishes when the individual treatment effects are constant. Otherwise, I should use the conservative type of covariance matrix.

The decomposition of the weighted individual treatment effect is then given by

$$\tau_i(sr, \mathbf{X}_i) = \sum_{j=1}^{D_{\max}} w^j \tau_i^{j,0}(sr, \mathbf{X}_i) = \sum_{j=1}^{D_{\max}} w^j \psi^{j,0} \cdot sr_i + \mathbf{X}_i' \sum_{j=1}^{D_{\max}} w^j \gamma^{j,0} + \sum_{j=1}^{D_{\max}} w^j \nu_i^{j,0}$$

with $\tau_i(sr, \mathbf{X}_i) = \sum_{j=1}^{D_{\max}} w^j Y_i^j(sr, \mathbf{X}_i) - Y_i^0(sr, \mathbf{X}_i)$. In this case, according to Proposition 1.6.1, I can recover $\psi_{ace}(\mathbf{X}_i) = \nabla_{sr}\tau(sr, \mathbf{X}_i) = \nabla_{sr}\mathbb{E}\left[\tau_i(sr, \mathbf{X}_i) \mid sr, D_i, \mathbf{X}_i\right]$ using a linear model with treatment interaction:

$$\text{Migrate}_i = \alpha + \beta_1 \text{Sex Ratio}_i + \beta_2 \mathbf{1}\{D_i \neq 0\} + \psi\left(\text{Sex Ratio}_i \cdot \mathbf{1}\{D_i \neq 0\}\right) + \mathbf{X}_i'\gamma + u_i.$$

Hence, the average causal effect of interest $\psi_{ace}(\mathbf{X}_i)$ can be identified as the weighted sum of the partial derivative of the systematic treatment effect variation with respect to the sex ratio $\sum_{j=1}^{D_{\max}} w^j \psi^{j,0}$.

1.7 Main Results

In this section, I report empirical evidence on the connection between the local sex ratio and the labor migration outcome of unmarried rural women with different male sibling structures.

1.7.1 Extensive Margin Comparison

I begin the analysis by examining whether the response of rural women's labor migration behavior to local sex ratios is affected by the presence of male siblings. Figure 1.11 plots the estimated work migration probability against the county-specific sex ratio for the age cohort 12-20 for rural women with brothers and those without brothers, respectively. From the graph, we can see that there is a strong and positive relationship between the local sex ratio and the propensity to participate in migratory work among rural women who have brothers. However, the migration decision of a rural woman who does not have brothers appears to be uncorrelated with the local sex ratio. It is also worth noting that the difference in the expected labor migration outcome between the two groups of rural women is relatively small in a low sex ratio environment, but it widens rapidly as the sex ratio becomes more skewed towards males.

Figure 1.12 presents the marginal effect of the local sex ratio on labor migration status for the two types of rural women, respectively. All parameters are estimated by a probit model which includes provincial fixed effects given by

$$\text{Migrate}_{icp} = \alpha + \beta \text{Sex Ratio}_{cp} + \mathbf{X}'_{icp}\gamma + \mathbf{W}'_{cp}\delta + \eta_p + u_{icp}$$

where Migrate_{icp} is the migration status of rural woman i in county c of province p, which is a dummy variable equal to one if the woman migrated for work in the survey year; Sex Ratio_{cp} is the measure of local sex ratio for county c of province p; $\mathbf{X}_{icp}$ is a vector of variables for the woman's personal and background characteristics; $\mathbf{W}_{cp}$ represents a set of county-level controls; η_p captures the provincial fixed effects and u_{icp} is the error term.

Model 1 is the parsimonious specification without the set of controls capturing important individual and household characteristics, as well as county-specific heterogeneities. In line with expectations, the coefficient estimate on the county-level sex ratio is positive and statistically significant at the 1% level. Specifically, I find that increasing the local sex ratio from the biologically normal level 1.05 to the average level 1.15 raises the probability of working outside the hometown by 4.35 percentage points for rural women who have brothers. Because the national average labor migration rate for this group of rural women is about 20%, this effect is economically sizable and equivalent to a 22% increase in the likelihood of becoming a migrant worker. In contrast, the local sex ratio effect reduces substantially to nearly zero and lacks statistical significance for rural women without brothers. This finding is consistent with my hypothesis that the positive correlation between the county-level sex ratio and rural female labor migration decision is mainly driven by the motive of rural women to financially support their brothers.

In Model 2, I control for various individual characteristics that may be relevant for a rural woman's labor migration decision: years of schooling, age, a quadratic term of age, birth order, a Han ethnicity dummy and self-reported health. In addition, the migration choice could also be influenced by different dimensions of family background. For example, the need to take care of elderly parents may hinder a rural women from working outside the home village. I thus add variables for parental health conditions in Model 3. I also include parental years of schooling to capture the role of family socioeconomic status or family culture. Model 4 further adjusts for average household wealth and household size because rural women growing up in a poorer and larger family may have a stronger incentive to raise income through labor migration.

The inclusion of these additional controls delivers point estimates on the local sex ratio that are comparable to those in Model 1 for rural women with brothers. Moreover, the coefficient remains robustly significant at the 1% level across alternative specifications. While the coefficients are larger in absolute value compared to Model 1 for rural women who have no brothers, the effect becomes negative once I add parental characteristics, and never achieves statistical significance in all three cases.

Since the prevalence of parental sex selection could be associated with regional development, some might worry that the female labor migration response to local sex ratio imbalance is indicative of the influence of local economic characteristics. To deal with this concern, I include a set of covariates described in Section 5 to control for county-specific economic conditions, as reported in Model 5. As can been seen, the addition of the county-level variables does not drastically alter my conclusion. The marginal effect of the local sex ratio still retains sign and significance for rural women with brothers, albeit with an even larger magnitude. Again, no significant relation is found for those without brothers.

Another potential threat to validity is that rural women without brothers tend to come from single-child families and thus are less likely to migrate due to the responsibility of caring for elderly parents. I attempt to exclude this possibility by limiting my sample to rural women growing up in families with two children and three children, respectively[20]. Figure 1.13 reports the corresponding estimates, which reveal similarly stark contrast between the two types of rural women. In Figure 1.A2, I perform the analogous estimation exercise but

[20]I do not consider families with more than three children as they constitute less than 10% of the families in my sample.

fix the number of daughters, which leave my results fundamentally unchanged.

To further confirm the differential patterns documented above, I next investigate how the overall treatment effect of having brothers, which is constructed in the conceptual framework, changes with the local sex ratio. To do this, I pool the two groups of rural women into a single regression by incorporating an interaction term of a sibling dummy for whether the woman has any brothers and the county-level sex ratio as follows

$$\text{Migrate}_{icp} = \alpha + \beta_1 \text{Sex Ratio}_{cp} + \beta_2 D_{icp} + \psi \left(\text{Sex Ratio}_{cp} \cdot D_{icp} \right) + \mathbf{X}'_{icp}\gamma + \mathbf{W}'_{cp}\delta + \eta_p + u_{icp}$$

where D_{icp} is an indicator for whether the rural woman has brothers or not. The coefficient ψ on the interaction variable Sex $\text{Ratio}_{cp} \cdot D_{icp}$ captures the difference in the impact of local sex ratio on the propensity to migrate for work between the two groups of rural women. A significantly positive estimate for ψ would provide supportive evidence for my hypotheses.

I now treat the male sibling indicator as exogenous, and I will later address the potential endogeneity of sibling structure for the purpose of robustness. The results shown in Figure 1.14 paint a consistent picture as those in Figure 1.12. The coefficient on the interaction variable is strongly positive and statistically significant at the 1% level. Conditioning on the full set of controls, a rural woman is 6.9% more likely to migrate for work if she has brothers than if she has no brothers in response to a 0.1 increase in the local sex ratio.

Some of the other covariates also give rise to the expected sign and significance[21]. For example, rural women's migration probability exhibits an inverted U shaped trend over age: it first increases until at the age of around 23 and then declines gradually to zero at the age of about 47. The interpretation is intuitive. Rural females may migrate less after they reach prime marriageable age and tend to settle down in the local place. Household wealth has a negative effect on the rural female's work migration choice, though it is rendered insignificant when I add the local controls. I also find that the local nonagricultural employment opportunities, proxied by number of firms per capita, are negatively correlated with the intention to migrate.

[21]Full results are available upon request.

1.7.2 Intensive Margin Comparison

The previous analysis has established that rural women having brothers exhibit an increased propensity to migrate for work in regions with a more unbalanced sex ratio. With particular focus on this type of rural women, I next probe into how the positive link responds to different male sibling structures. To begin with, I look to see if the impact of the local sex ratio is more pronounced with a larger size of male siblings. In Figure 1.15, I plot the estimated probability of labor migration against local sex ratios for rural women with one brother and those with multiple brothers, respectively. The figure clearly reveals a positive association between the county sex ratio and the expected labor migration status for both groups. I also note that for almost all local sex ratios, rural women with two or more brothers are much more likely to become a migrant worker than rural women with only one brother, and they react more sensitively to changes in the sex ratio.

To facilitate comparison, in Panel A of Figure 1.16 I estimate the marginal effect of the local sex ratio by performing separate regressions for the two groups of rural women. As shown, the effect is strongly statistically significant as well as economically important in each group, though it is markedly larger in magnitude among rural women who have more than one brother. In particular, a 0.1 increase in the local sex ratio leads to a 10.83 percentage point increase in the likelihood of labor migration if the rural woman has multiple brothers, compared to 2.82 percentage points if the rural woman has a single brother. Panel B displays the corresponding estimates obtained from the pooled regression, which prove similar to those in Panel A. In an additional exercise, I explore the role of male sibling size by interacting the local sex ratio with the number of brothers that the rural woman has, as summarized in Appendix Figure 1.A3. The coefficient on the interaction term is consistently positive and significant across different model specifications, suggesting that the link from the sex ratio imbalance to female labor migration behavior is stronger if the rural woman has a larger number of brothers. Figure 1.17 confirms this pattern by depicting the local sex ratio effect under different male sibling structures: zero brother, one brother and more than one brother. These results are in accordance with my story. In either channel, rural women having more brothers are incentivized to migrate more when faced with a higher local sex ratio in an effort to improve their brothers' welfare.

In a similar vein, I assess the importance of the relative male sibling size. Appendix Figure 1.A4 and Figure 1.A5 present the point estimates for rural women with more brothers than sisters and rural women with more sisters than brothers. I observe a weaker local sex ratio effect among rural women with a smaller size of male siblings relative to female siblings. This is the case because having more sisters who also provide monetary support for brothers could help alleviate these rural women's financial burden and thus reduce their willingness to migrate.

I finally look at whether the labor migration response is affected by birth order. A central value in traditional Chinese family culture is that elder siblings bear the obligation to take care of and offer assistance to younger siblings when needed. As might be expected, the local sex ratio would have a stronger impact on rural women with younger brothers. To verify this, Figure 1.18 first relates the migration choice to the local sex ratio and the full suite of control variables for rural women who have only elder brothers and those who have only younger brothers, respectively. As it turns out, rural women with only younger brothers are indeed more responsive to the local sex ratio than their peers with only elder brothers in migration behavior. I see that the propensity to migrate increases by 7.6 percentage points with a 0.1 rise in the county sex ratio if the rural woman has only younger brothers, and 4.6 percentage points if she has only elder brothers. I repeat the same exercise comparing rural women who are younger than the average age of their brothers and those who are older than the average age of their brothers, which points to similar conclusion. Figure 1.19 further describes the local sex ratio effect under different age gaps for those with only younger brothers. The estimates are obtained by augmenting the specification with interactions of the local sex ratio and dummy variables for the age difference between the rural woman and her youngest brother. As shown, the larger the age gap, the more likely the rural woman emigrates to urban areas for work in response to a rise in the local sex ratio. When the rural woman is 8 or more years older than her youngest brother, a 0.1 increase in the local sex ratio raises her probability of working outside the hometown by about 40 percentage points.

Collectively, my findings indicate that rural women who have a larger number of brothers or who have younger brothers respond more strongly to increases in the local sex ratio. The differential effects may stem from the heavier economic burden of supporting more brothers, or the family responsibility for elder siblings to help younger siblings.

1.7.3 Robustness

In the following, I implement a battery of robustness tests.

1.7.3.1 Different Labor Migration Measure

The first sensitivity test is related to how labor migration is defined. In my discussion above, the dependent variable is an indicator for whether the rural woman has been working outside the home village in the survey year. One concern is that rural women's incentive to migrate may not be adequately captured by their current migration status, as they might have spent a huge amount of time involving in migratory work in previous years but are temporarily on leave for the present. I therefore replicate the main part of my analysis but replacing the migration variable with the measure for former labor migration experience. More concretely, the outcome variable is now a dummy for whether the rural woman has ever migrated for work.

As illustrated in Figure 1.20, I find a positive and significant effect of the local sex ratio on migration outcomes only among rural women with brothers. Though slightly smaller in magnitude, the coefficient appears to be more stable relative to the previous estimates. I also reestimate the pooled regressions in Figure 1.21, which yield essentially the same patterns.

1.7.3.2 Different Sex Ratio Measure

I next consider whether my major findings are robust to alternative measure of the sex ratio. In the main analysis, I focus on the population aged 16 to 20 when calculating the local sex ratios. Although I believe that the sex ratio for this premarital group reflects the marriage market prospects expected by the households, some might argue that it is not informative of the current marriage market conditions for those who are ready to find a spouse. To mitigate this concern, I construct the county-level sex ratios for the cohorts between the ages of 16 and 25[22].

Using the new sex ratio measure, I repeat the specification based on the full sample with all covariates included. For the rest of the robustness tests, I employ the same empirical setup for simplicity[23]. The results are presented in Figure 1.22. Reassuringly, the economic size and statistical significance of the local sex ratio effect are almost identical to my principal estimates.

1.7.3.3 Younger Cohorts of Rural Women

Since the average marriage age among rural females is around 22, one might speculate that those who are relatively old but still remain single are not representative of the population of Chinese rural women. Another concern is that the skewed local sex ratios could also weaken the incentive to migrate for rural women who are at the prime marriageable age in light of the improved marriage market conditions towards women. I then restrict my sample to younger cohorts of females to gauge the robustness of my estimates to these issues.

Figure 1.23 plots the results when I exclude rural women who are older than 22 and 25, respectively. The estimated coefficients are somewhat attenuated, but retain sign and significance, and also similar in magnitude to earlier results.

1.7.3.4 Potential Endogeneity: Sibling Variable

A major threat to identification is that the gender composition of siblings might be correlated with unobservable household characteristics that also affect the rural woman's propensity to migrate. If this were the case, the endogenous male sibling structure could undermine the

[22] I repeat the exercise by recalculating the sex ratio for the age cohorts 16-27, 16-30, 18-25, 18-27 and 18-30, respectively. The estimated coefficient is little disturbed when I change the measure for the local sex ratio. Results are available upon request.

[23] Splitting the sample by whether the rural woman has brothers yields similar results, which are not reported to save space and available upon request.

comparison of rural females with brothers and those without brothers. In an effort to address the potential endogeneity, I employ an instrumental variable approach as illustrated in the conceptual framework. More precisely, I make use of the exogenous variation in the number of brothers that the parents ever have conditional on the total number of their siblings. I consider four possible instruments for the male sibling indicator: the number of the father's brothers Z_i^f, the number of the mother's brothers Z_i^m, the total number of the parents' brothers $Z_i^t = Z_i^m + Z_i^f$ and the instrument with assigned values Z_i[24].

Before turning to the IV estimates, I first check to further make sure that my instrumental variables satisfy the identifying assumptions in relation to exclusion restriction, independence and monotonicity. To this end, I conduct the specification test for instrument validity proposed by Kitagawa (2015). The central idea of the test is to infer the testable implications under instrument validity using a variance-weighted Kolmogorov–Smirnov statistic[25]. The results of the test are reported in Table 1.2. Here ξ is a user-specified trimming constant in the test statistic ensuring nice statistical properties. As recommended by Kitagawa (2015), I set ξ to be 0.05 and 0.1. In Columns 1 and 2, I present the bootstrap p-values of the test for the case with no covariate. I find that all of them are larger than the 10 percent significance level and some are even close to 1. Besides, the p-values are insensitive to the choices of ξ. The results remain unaltered when I control for covariates, as displayed in Columns 3 and 4. Hence, I do not empirically reject the null that my instruments are credible.

I now discuss the IV results. Figure 1.24 shows the first-stage relationship for instrument relevance. I observe that whether a rural woman has male siblings is positively and strongly associated with the fraction of brothers that her parents ever have. Figure 1.25 plots the IV estimates of the local sex ratio effect. As can be seen, regardless of which instrumental

[24]When I construct Z_i, I assume that the size of the father's male siblings is more important than that of the mother's in determining the number of brothers of the rural woman. To check robustness, I consider the opposite case and assign larger values to the instrument vector if the mother has ever had more brothers conditional on the total number of parental siblings. On the other hand, over 90% of the parents in my sample have 3 or fewer brothers. In another sensitivity test, the parental male sibling size variables are recoded and censored at 4 if they are larger than 4. Reported inFigure 1.A8, the results remain almost unchanged.

[25]The technical details of the test are summarized in the appendix.

variable I use, my results confirm the statistically significant and positive effect of the local sex ratio on the labor migration decision for rural women having brothers and meanwhile, the lack of impact for those without brothers[26].

1.7.3.5 Potential Endogeneity: Local Sex Ratio

While the results thus far are consistent with my hypothesis, the remaining concern with respect to my estimates is that the local sex ratio effect could have been driven by some unobservable regional factors that might directly influence rural women's migration outcomes. For example, local sex ratios may be reflecting differences in regional development or culture which also result in differential female migration patterns (Cameron et al., 2017). Edlund et al. (2007), however, find evidence in favor of exogeneity of local sex ratios in China. Their findings suggest that geographical differences in China's sex ratio can mainly be accounted for by variation in the enforcement of the OCP across regions. Generally, the implementation of the OCP depends on population density, fertility rate as well as the eagerness of local officials to comply with central policies. There is no reason to expect that these lagged variables have direct impacts on household behavior at the current time.

However, I still attempt to instrument for the sex ratio measure as a final robustness check. To do so, I exploit the fact that the strictness of the family planning policy is an important determinant of the local sex imbalance. Specifically, in a stricter OCP regime with harsher financial penalties, the cost of violating the policy is relatively expensive; as a result, residents are more likely to practice sex selection in order to have at least one son. Against this background, an appropriate and also commonly used instrument for the sex ratio is the fertility fine for extra births set by the regional government. Following Ebenstein (2010), I construct the average fertility fine in each county for the years when the corresponding cohorts in the calculation of local sex ratios were born.

For the identification method to work, the fertility fine should be uncorrelated with

[26]I repeat the exercise replacing the male sibling indicator with the number of brothers that the rural woman has. The results are summarized in Appendix Figure 1.A7, which reveal significantly positive effect of having an additional brother on the likelihood of participating in migratory work.

other county-specific variables affecting rural women's labor migration choice. Although it is very difficult to completely rule out this possibility, I tend to believe that this assumption holds in my setting. As argued in Edlund et al. (2007), policies implemented decades ago are unlikely to be correlated with the contemporaneous unobservables. In addition, the inclusion of county-level controls and provincial fixed effects in my specification also helps assuage this concern.

The instrumented results displayed in Figure 1.26 continue to reveal distinct sex ratio effects under different sibling structures. The estimated coefficient on the local sex ratio is still positive and statistically significant for rural women having brothers, although the effect size is larger compared to that reported in my main analysis. Again, I do not find any significant relationship for those without brothers.

1.7.4 Prefecture-level Evidence: How Much of the Increase in Rural Women's Labor Migration Rate Could be Explained by the Rising Sex Ratios?

So far I have discovered a positive, significant, and apparently robust impact of the local sex ratio on the decision to migrate for work only among rural women having brothers. One natural and important question to ask is whether the rising sex ratio could explain the recent increase in female labor migration rate in rural China. To answer this question, I next analyze how the changes in the sex ratio contribute to the changes in rural women's labor migration rate over time.

Table 1.3 examines the effect of the sex ratio on female labor migration rate using the prefecture-level panel data spanning 1990 and 2000. In Columns 1-2, the dependent variable is the labor migration rate for unmarried rural women aged 16-30, and the independent variable of interest is the sex ratio for the age cohort 16-20. Column 1 only controls for year fixed effects and provincial fixed effects. The coefficient 0.163, which is statistically significant at the 1% level, implies that rural women's labor migration rate increases by 1.63 percentage points in response to a 10 percentage point increase in the local sex ratio. To avoid the possibility that the positive relationship is spurious, I add a series of prefecture-level covariates in Column 2, including GDP, outputs in industrial and service sectors, total population and high school enrollment, all measured in per capita value except total population. The estimated effect remains highly significant with an even larger magnitude (0.229). According to China Population Census, the average female labor migration rate increases from 2.1% in 1990 to 9.9% in 2000, and the average sex ratio increases from 1.044 to 1.175 in the same period. This suggests that the rising sex ratio could account for around 38.5% of the increase in the proportion of unmarried young females working outside the hometown from 1990 to 2000 in rural China.

For robustness, I consider the age cohort 16-50 for calculating the female labor migration rate in Columns 3-4, and measure the local sex ratio for the age cohort 16-25 in Columns 5-6. I again find evidence similar to the previously reported results.

1.8 Mechanisms

My main results in Section 7 suggest that the local sex ratio imbalance induces unmarried rural women having brothers to participate more in migratory work, while it does not have any noticeable impact on those having no brothers. I have proposed two candidate mechanisms—— the son preference mechanism and the marriage market competition mechanism—— through which the local sex ratio affects the two types of rural women's labor migration behavior differently. In this section, I aim to discuss which channel is more likely to be the underlying mechanism in linking the migration outcomes of rural women with brothers to the regional sex ratio.

1.8.1 Placebo Test

According to my story of the son preference channel, the local sex ratio effect is at least due in part to the correlation between the intensity of son preference and rural women's migration behavior. To distinguish the marriage market pressure effect from the son preference effect, I perform a placebo test by replacing the premarital age group sex ratio with the sex ratio for older cohorts that have little influence on the current marriage market competition. The key idea is that cultural norms and underlying values, such as son preference, are deeply rooted in regional history and tend to evolve very slowly (Roland, 2004). If my main results are really driven by geographical differences in the degree of son preference, then one might expect the older generation sex ratio to explain rural women's migration choice in a similarly significant and powerful way.

Figure 1.27 reports the results of reestimating the pooled regression with all controls and the sex ratio for the local population aged between 66 and 70. As can be seen, the coefficient on the local sex ratio for both rural women with brothers and those without brothers is several times smaller and statistically indistinguishable from zero[27]. The results from this placebo test do not support the hypothesis that the local sex ratio effect documented in Section 7 is simply attributable to the role of regional son preference culture.

1.8.2 Does Marriage Market Pressure Explain the Local Sex Ratio Effect?

Under the marriage market mechanism, the local sex ratio effect arises from rural women's motives to increase the male siblings' financial attractiveness as well as their chances of finding a bride. If this were true, I would observe a weaker impact of the local sex ratio among rural women who do not have unmarried brothers. To formally test this, I restrict my attention to rural women with brothers and examine whether the local sex ratio effect varies by the marital status of brothers. Consistent with the marriage market channel, the estimated coefficient is positive and statistically significant at the 1% level for rural women having unmarried brothers. In contrast, there is no significant relationship between the county sex ratio and migration outcomes among rural women with only married brothers.

To further bolster confidence that the local sex ratio effect operates through the pathway of marriage market pressure, I then investigate how the presence of a migrant sister affects rural men's marriage and labor migration probabilities. If the local sex ratio indeed captures the intensity of competition for brides, then rural men growing up in regions with a scarcity

[27] The results are essentially identical if I use the local sex ratio measure for other older age cohorts, including 36-40, 46-50, 56-60, and 76-80.

of females would be less likely to get married and more likely to migrate for work with the hope of improving their own standing in the marriage market. One implication of this avenue is that other things equal, having a migrant sister who is able to raise household income would mitigate the adverse impacts of the local sex imbalance on rural men.

I test this prediction in Figure 1.29 using the sample of rural men who are above 22[28]. I first estimate the probability of being married as a function of the local sex ratio and its interaction with a dummy variable for whether the rural man has a migrant sister, and other controls that mirror those in the analysis for female labor migration. Panel A of Figure 1.29 plots the coefficient on the local sex ratio for rural men with migrant sisters and those without migrant sisters, respectively. I find that a rise in the local sex ratio is associated with a significantly lower likelihood of being married for rural men without migrant sisters, but the effect is insignificant for those having migrant sisters. In Panel B, I repeat the same specification with the indicator for the rural man's migration status as the dependent variable. As expected, compared to rural men who have no migrant sisters, those with migrant sisters have a significantly weaker incentive to migrate in response to an increase in the local sex ratio. I interpret the results of this analysis as corroborative evidence for the marriage market mechanism.

1.8.3 Decomposition of the Local Sex Ratio Effect

The preceding discussion confirms the importance of the marriage market mechanism in explaining the effect of male-biased sex ratios on rural women's labor migration decisions. As noted earlier, the intensified mating competition, triggered by the surplus of males, has led to the rise in marriage expenses. In order to secure a wife, the groom's family is often required to pay a higher bride price and more importantly, to purchase an apartment or build a house for the newlywed. This, in turn, has pushed up the housing prices and places greater financial pressure on households with sons (Wei et al., 2017).

[28]In China, the legal age to marry for men is 22. I also perform the same exercise with the sample of rural men aged above 16 and 20, respectively. The results remain almost unchanged.

To gain additional insight into the marriage market channel, I next explore the extent to which my main estimates are driven by differences in marriage expenditure and housing price across regions. Following the standard causal mediation analysis approach (e.g., Gong et al., 2018; Imai et al., 2010; MacKinnon et al., 2002), I decompose the local sex ratio effect into components attributable to the increased marriage expenses and housing prices, and components induced by other factors. That is, I treat marriage expenditure and housing price as two important mediators that lie in the pathway between the local sex ratio and rural women's migratory work behavior. Specifically, I estimate a set of causal parameters described by Figure 1.30. Here, α represents the causal effect of the local sex ratio on rural women's labor migration outcomes given the individual and local economic characteristics (the local sex ratio effect); β_1 and β_2 capture the influence of the local sex ratio on the local marriage expenses and the local housing price, respectively; γ_1 and γ_2 are defined as the causal effects of marriage expenses and housing price on rural women's labor migration choice conditional on all background variables, respectively. The explanatory power of marriage expenditure and housing price can then be separately approximated by $\beta_1\gamma_1/\alpha$ and $\beta_2\gamma_2/\alpha$, while $(1 - \beta_1\gamma_1/\alpha - \beta_2\gamma_2/\alpha)$ is the share explained by all other factors.

In this exercise, I focus on the sample of rural women with brothers, and make use of two additional data sources: the marriage expenses are constructed from the 2014 CLDS survey and the data on housing prices come from the 2005 China Population Census. Figure 1.31 presents my decompositions of the local sex ratio effect. In the first bar, I measure the local marriage expenditure as the average financial cost paid by the groom's family for all marriage-relevant events based on the sample of rural men who were married in the corresponding RUMiC survey year. The local housing price is computed as the mean housing value for the residential homes purchased in 2004 or 2005. I find that 34.40% of the local sex ratio effect can be explained by increases in marriage expenses, and housing price accounts for 23.12% of the effect. The two factors together contribute to 57.52% of the local sex ratio effect. The decomposition results remain robustly intact when I use alternative measures of marriage expenses (five-year average around the survey year) and housing price (average housing value per squared meter), as shown by the second and third bars.

To summarize, the mediation analysis provides evidence suggesting that increases in marriage-related expenditure and housing price brought about by the male surplus can explain around 50% of the local sex ratio effect observed among rural women having brothers. These results reinforce my previous findings that the marriage market competition mechanism is likely to be responsible for the positive link between the sex ratios and the labor migration behavior of rural women with brothers.

1.9 Conclusion

Over the past few decades, China's rural-to-urban migrant population has transformed from a male-dominated structure into one that is nearly gender-balanced. Standard economic explanations have mainly centered on the expansion of non-agricultural sectors and marriage migration. This paper contributes to the literature by shedding light on the role of the sex ratio imbalance as an additional force shaping the recent feminization of internal migration in China.

I propose the idea that sex ratios are positively associated with unmarried rural women's labor migration behavior. Two possible stories have been developed to account for this relationship——one having to do with the son preference, and the other with the marriage market pressure. First, I argue that the sex ratio may represent the degree of son preference and thus could be informative of how much rural women care about their male siblings. The logic of this channel is that rural women are more likely to migrate as a means to raise household income when they place a higher value on the welfare of their brothers. Alternatively, it may also happen that the increased competition for brides prompts rural women having brothers to migrate with the aim of improving the financial attractiveness of their brothers in the marriage market. While the favorable marriage market conditions towards women could lead to a weaker incentive to migrate for those without brothers, they may not reduce their migratory labor supply due to the intention to enhance bargaining power after marriage.

Using the RUMiC survey data combined with China Population Census, I find that rural women with brothers exhibit a higher propensity to migrate in regions with a more skewed sex ratio. The effect size is large and robust. Specifically, a 0.1 rise in the local sex ratio increases the probability of becoming a migrant worker by 4.35-6.84 percentage points for rural women with brothers, which is equivalent to a 22-34% increase in the labor migration rate. However, no significant effect is seen among those who do not have brothers. Moreover, I show that the local sex ratio effect is stronger when the rural woman has multiple brothers or when the brothers are relatively younger. I also discover that around 38.5% of the increase in rural female labor migration rate from 1990 to 2000 could be explained by the local sex ratio effect. Examining the mechanisms that drive my results, I find evidence consistent with the marriage market pressure story.

My findings have a number of important implications for researchers and policymakers. First, my results can be used to broaden our understanding of the determinants of female labor migration dynamics in contemporary China. Second, my study extends the unintended consequences of the OCP to the labor market domain by providing a plausible link from the sex ratio imbalance to unmarried rural women's migratory work decision.

My work also offers insights into gender inequality and women's socioeconomic outcomes in rural China. Despite the resulting improved position of rural women in the marriage market, the male-biased sex ratio may exert negative influences on those having male siblings. For example, in response to the rising sex ratio, households with both sons and daughters might reduce parental inputs into daughters but increase investment in sons with the hope of enhancing the sons' likelihood of finding a spouse. More research is needed to explore the effect of the unbalanced sex ratio on rural women's cognitive and noncognitive outcomes. It would also be interesting to study how the sex ratio imbalance affects the educational attainment and the subsequent labor market performance of rural females.

My paper suggests that rural women's labor migration incentive stems from the need to contribute to the economic well-being of their brothers. Follow-up studies that utilize intra-household remittance data will provide significant evidence to substantiate my hypothesis and further pin down the underlying pathways. Finally, my findings may not be applied to the setting of rural China only. Future research could extend my results to other countries with severe sex ratio imbalance to see whether there is a similar connection between the local sex ratio and female labor market behavior.

Tables

Table 1.1 Summary Statistics of the Main Variables

Variable	Full sample			With brothers			Without brothers			K-S test	
	Obs	Mean	S.D.	Obs	Mean	S.D.	Obs	Mean	S.D.	D-stat.	p-value
Migration status	1923	0.578	0.494	1155	0.624	0.485	768	0.508	0.500	0.106	0.005
Migration exper.	1924	0.686	0.464	1137	0.719	0.449	787	0.638	0.481	0.076	0.092
Education	1988	9.201	2.378	1135	8.862	2.272	853	9.653	2.442	0.134	0.000
Age	2477	21.48	3.636	1522	21.21	3.203	955	21.91	4.202	0.066	0.195
Ethnicity	2474	0.991	0.096	1522	0.992	0.088	952	0.988	0.107	0.003	1.000
Health	2476	4.275	0.664	1521	4.287	0.659	955	4.255	0.673	0.021	1.000
Father health	2429	3.926	0.782	1494	3.941	0.784	935	3.902	0.780	0.041	0.757
Mother health	2430	3.777	0.853	1495	3.779	0.838	935	3.774	0.878	0.036	0.879
Father education	2348	7.545	2.134	1427	7.551	2.100	921	7.535	2.186	0.040	0.779
Mother education	2078	6.511	2.253	1250	6.435	2.236	828	6.624	2.275	0.067	0.183
Family wealth (pc)	2429	1.544	3.368	1490	1.268	1.465	939	1.981	5.063	0.100	0.009
Family size	2465	4.680	1.392	1511	5.110	1.350	954	4.000	1.169	0.359	0.000
Birth order	2476	2.023	0.993	1521	2.214	0.989	955	1.717	0.919	0.329	0.000

Notes: "S.D." is the abbreviation of "Standard deviation", "stat." is the abbreviation of "statistic", "exper." is the abbreviation of "experience", "pc" is the abbreviation of "per capita". The K-S test performs the Kolmogorov-Smirnov equality-of-distributions test between two groups, where D-statistic denotes the largest difference between the two distribution functions. The null hypothesis of the K-S test is that the distributions of a certain characteristic are identical between rural women with brothers and those without brothers.

Table 1.2 Test Results of Instrument Validity: Bootstrap p-Value

	No covariate		With covariates	
	(1)	(2)	(3)	(4)
	$\xi = 0.05$	$\xi = 0.1$	$\xi = 0.05$	$\xi = 0.1$
Number of father's brothers	0.764	0.764	0.806	0.806
Number of mother's brothers	0.162	0.162	0.226	0.226
Number of parents' brothers	0.440	0.440	0.624	0.624
Assigned instrument values	0.902	0.902	0.900	0.906

Notes: This table presents the bootstrap p-values of the specification test for instrument validity proposed by Kitagawa (2015). The null hypothesis is that the instrument satisfies the identifying assumptions regarding exclusion restriction, independence and monotonicity. ξ is a user-specified trimming constant in the test statistic ensuring nice statistical properties. The number of bootstrap replications 500.

Table 1.3 Effects of the Sex Ratio on Female Labor Migration Rate (Prefecture Level)

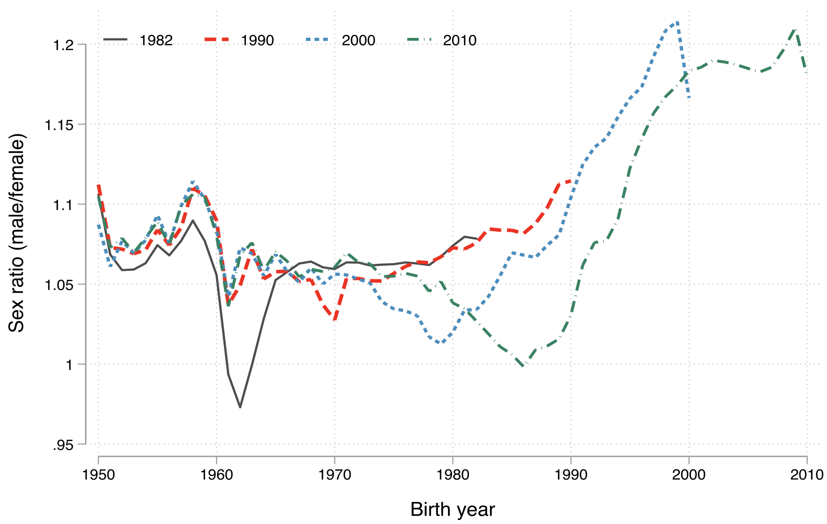
	Dependent variable: female labor migration rate					
Sex ratio/Migration cohorts	16-20 / 16-30		16-20 / 16-50		16-25 / 16-30	
	(1)	(2)	(3)	(4)	(5)	(6)
Sex ratio	0.163***	0.229***	0.163***	0.228***	0.144***	0.170***
	(0.013)	(0.016)	(0.013)	(0.016)	(0.018)	(0.021)
Controls	No	Yes	No	Yes	No	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Regional effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	823	706	823	706	823	706
R^2	0.673	0.716	0.672	0.715	0.637	0.660

Notes: Robust standard errors in parentheses. This table presents the effect of the sex ratio on female labor migration rate that is estimated using the prefecture-level panel data spanning 1990 and 2000. The local sex ratios and the female labor migration rates are constructed from the 1990 and 2000 China Population Censuses. In the calculation of the local sex ratio, I consider the age cohort 16-30 in Columns 1-4 and the age cohort 16-25 in Columns 4-5. In the calculation of the female labor migration rate, I consider the age cohort 16-20 in Columns 1-2 and 4-5, and the age cohort 16-50 in Columns 2-3. The control covariates are drawn from China statistical year books, including GDP, outputs in industrial and service sectors, total population and high school enrollment, all measured in per capita value except total population. The regional effects are captured by a set of provincial dummies.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

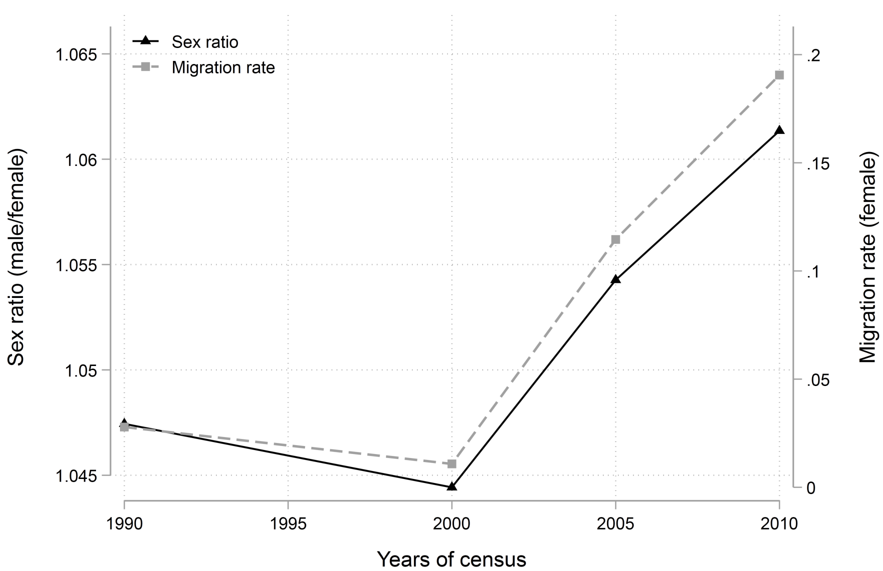
Figures

Figure 1.1 Sex Ratios at Birth in China



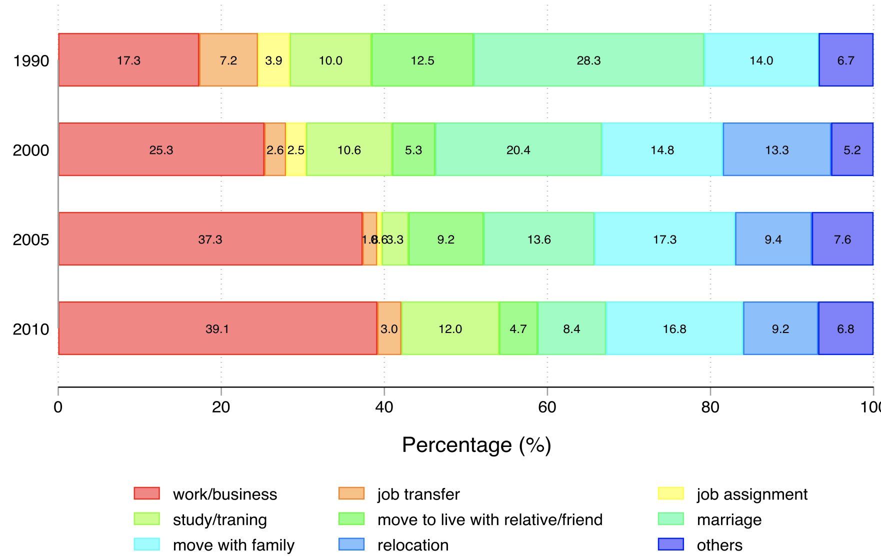
Notes: This figure shows sex ratios by birth year, which are calculated from the 1% sample of 1982, 1990, 2000 and 2010 China Population Censuses.

Figure 1.2 Trends in Sex Ratio and Female Migration Rate in Rural China



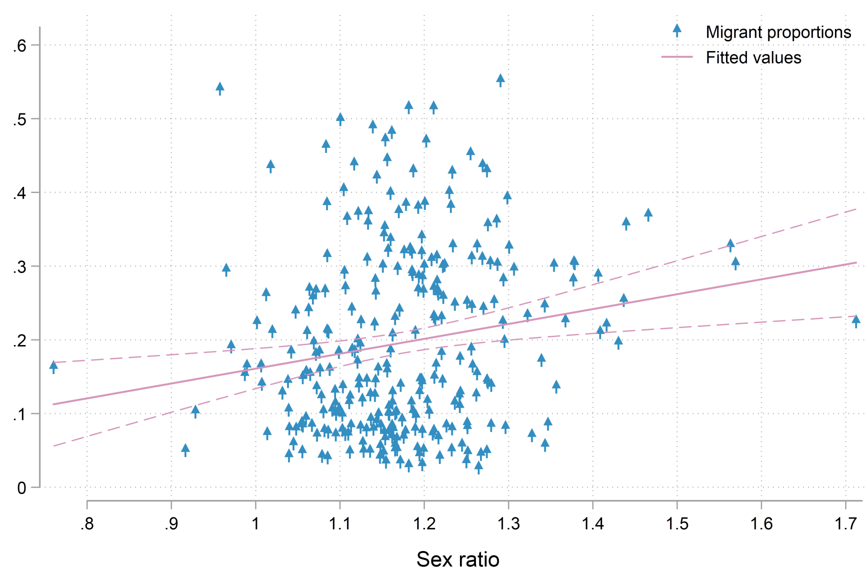
Notes: This figure shows the comovement between the sex ratio and the female migration rate for the premarital cohort aged between 16 and 20 over the period 1990-2010. The sex ratios and the female migration rates are calculated from the 1990, 2000 and 2010 China Population Censuses.

Figure 1.3 Self-reported Reasons for Female Migration in Rural China



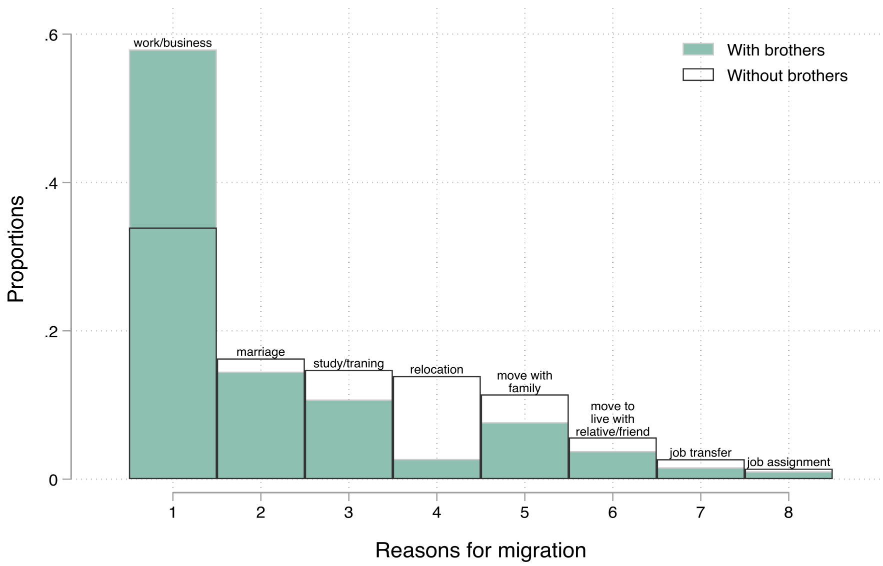
Notes: This figure decomposes the female migrant population by self-reported reason. It is shown that work-based migration has accounted for an increasingly significant proportion of the whole female migrant population over time. Data sources come from the 1990, 2000 and 2010 China Population Censuses.

Figure 1.4 Local Sex Ratios and Female Labor Migration in Rural China



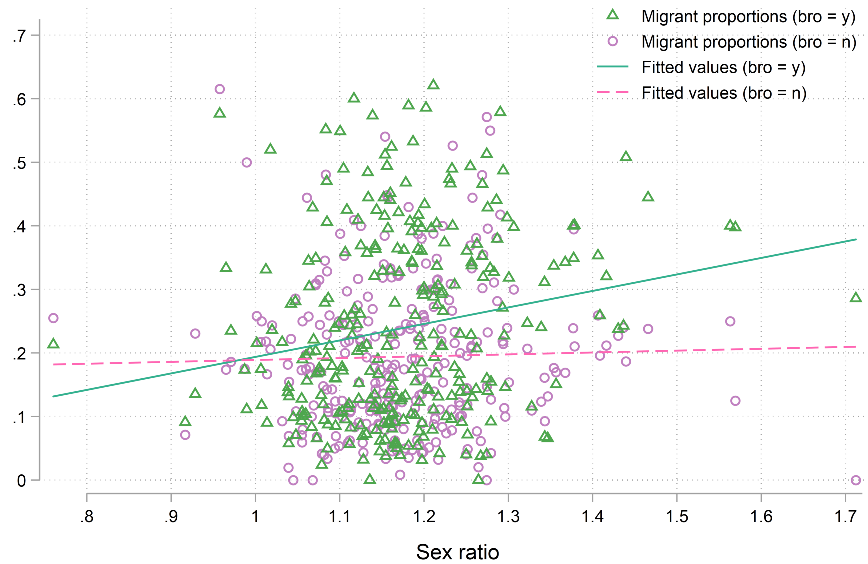
Notes: This figure plots the female labor migration rates against the sex ratios at the prefecture level. Each blue dot represents a prefecture. The solid line is the fitted line for the regression of the female labor migration rate on the local sex ratio and the dash lines constitute the corresponding 95% confidence interval. Data sources come from the 2005 China Population Census.

Figure 1.5 Self-reported Reasons for Female Migration in Rural China: Women with Brothers versus Women without Brothers



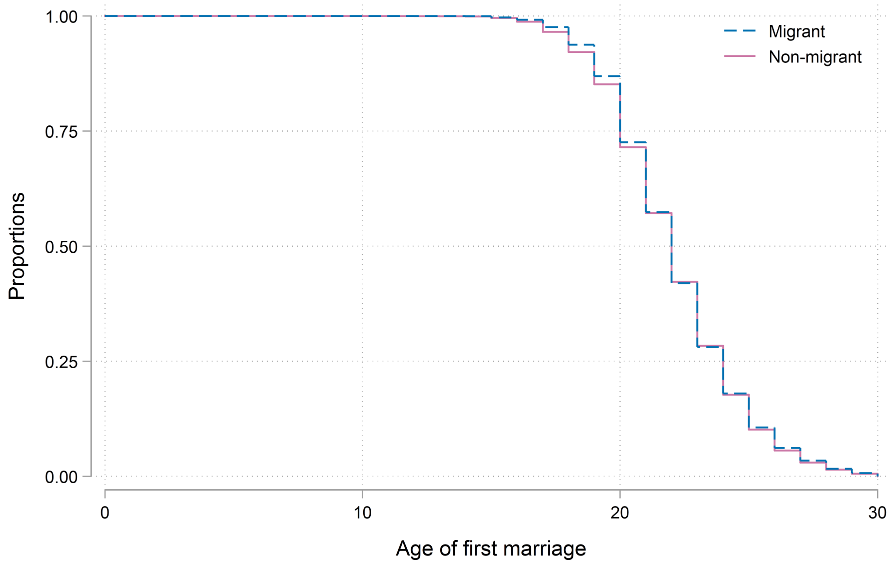
Notes: This figure presents the distributions of self-reported reasons for migration for rural women with brothers and those without brothers, respectively. It is shown that a much larger percentage of rural women having brothers report work or business as their primary reason for migration compared to those having no brothers. Data sources come from the 2005 China Population Census.

Figure 1.6 Local Sex Ratios and Female Labor Migration in Rural China: Women with Brothers versus Women without Brothers



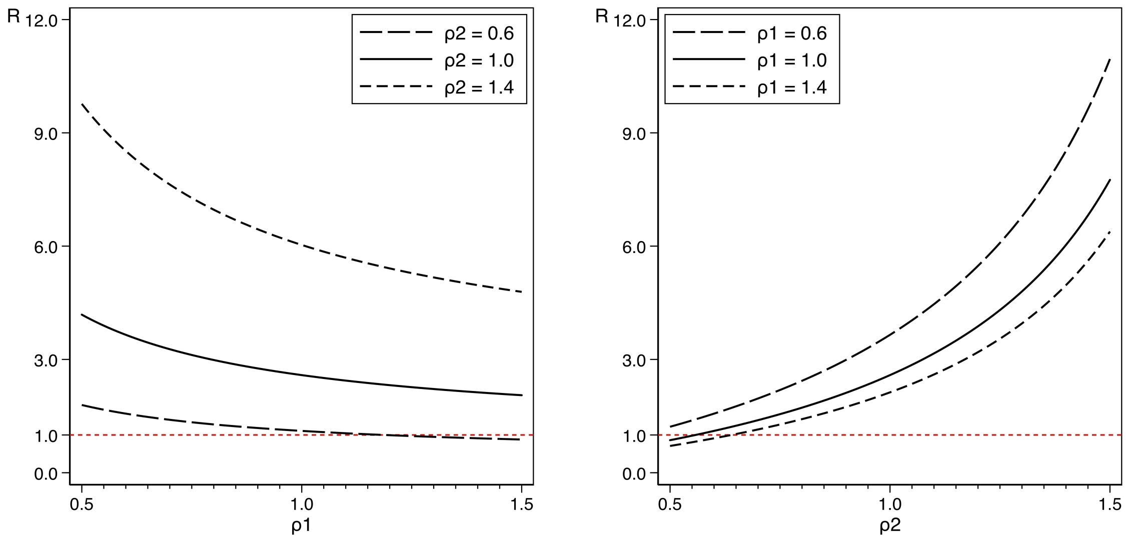
Notes: This figure presents scatter plots and fitted lines of the female labor migration rates against the sex ratios at the prefecture level for rural women with brothers and those without brothers, respectively. It is shown that the correlation between the local sex ratio and the female labor migration rate is considerably stronger and positive among rural women having brothers than those having no brothers. Data sources come from the 2005 China Population Census.

Figure 1.7 Survival Curves of First Marriage for Rural Women by Migration Status



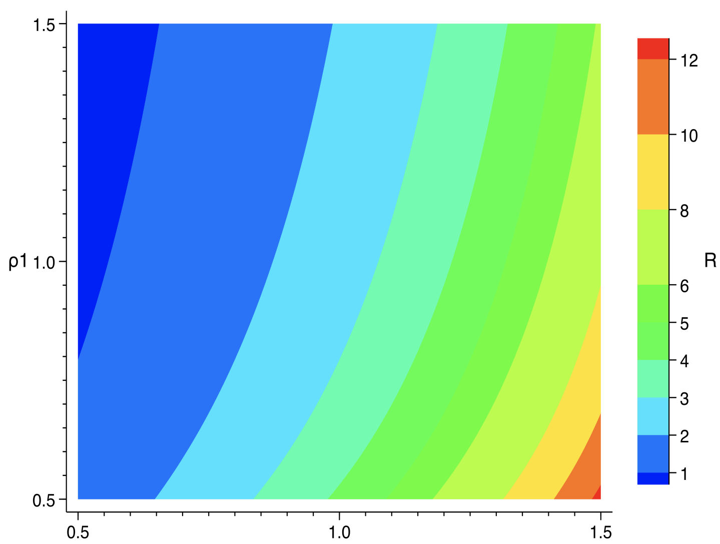
Notes: This figure plots the survival curves of first marriage for rural female migrants and non-migrants, respectively. The horizontal axis is the age of first marriage and the vertical axis is the proportion unmarried. It is shown that there is almost no difference in the chances of marriage over time between the two type of rural women. Data sources come from China Labor-Force Dynamics Survey (CLDS).

Figure 1.8 Relative Impacts of the Two Channels (One of ρ_1, ρ_2 Changes)



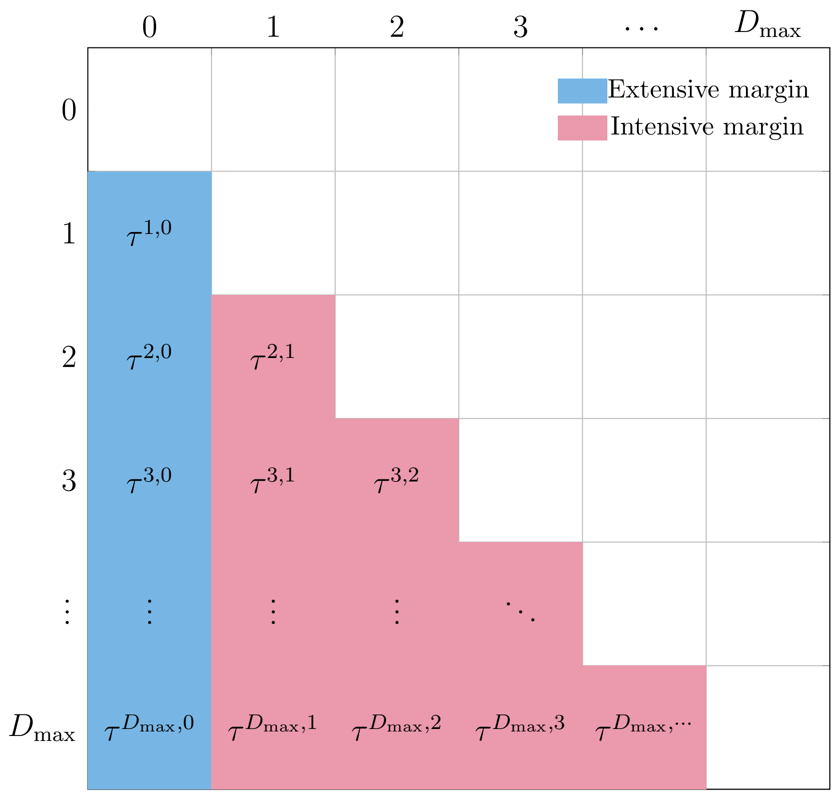
Notes: This figure shows how the relative ratio $\mathcal{R}$ changes if one of ρ_1, ρ_2 changes. I set $\alpha_d^c = 0.5$, $\alpha_d^\pi = 0.25$, $\alpha_d^\ell = 0.25$, $H_d = 0.6$, $\frac{I^{\max}}{I_0} = \frac{\beta\left(1-h_m^2\right)+w_f h_f+E_f+E_d}{I_0} = 2$.

Figure 1.9 Relative Impacts of the Two Channels (ρ_1, ρ_2 Change Simultaneously)



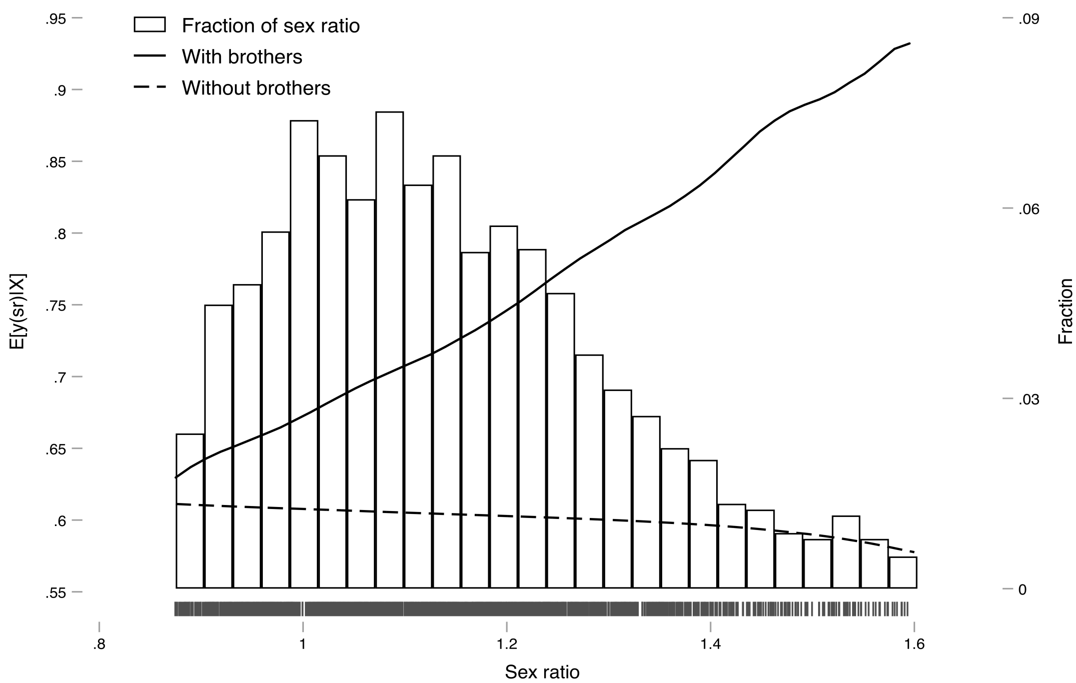
Notes: This figure provides a contour of the relative ratio $\mathcal{R}$ for different values of ρ_1, ρ_2. I set $\alpha_d^c = 0.5$, $\alpha_d^\pi = 0.25$, $\alpha_d^\ell = 0.25$, $H_d = 0.6$, $\frac{I^{\max}}{I_0} = \frac{\beta\left(1-h_m^2\right)+w_f e_f+E_f+E_d}{I_0} = 2$.

Figure 1.10 Extensive Margin & Intensive Margin



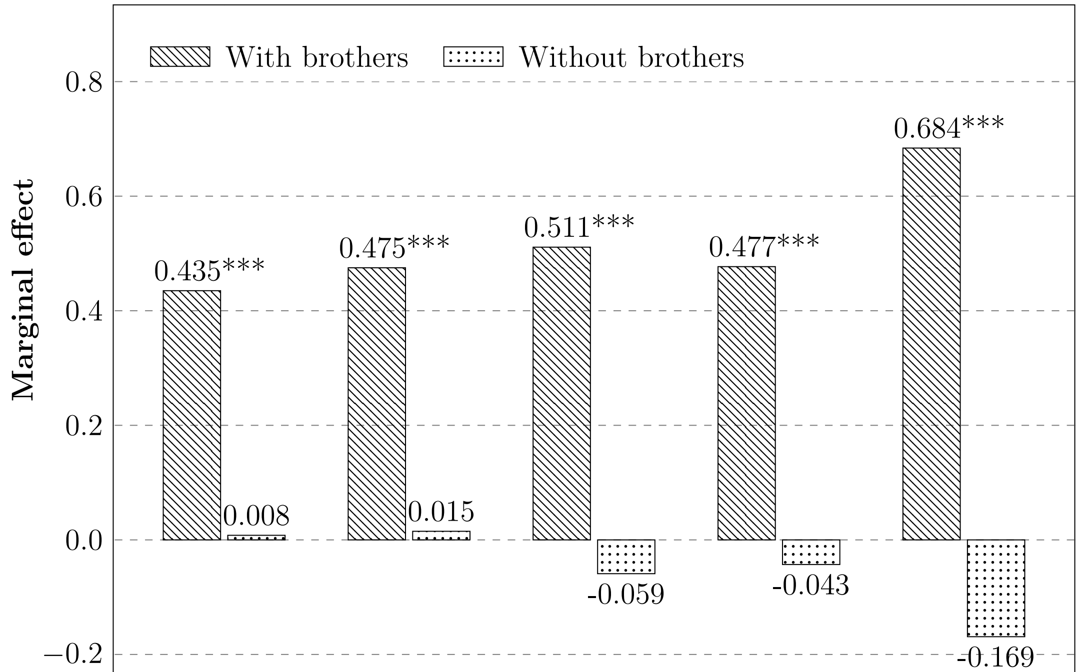
Notes: This figure shows the interpretation of the treatment effects at the extensive and intensive margins with different pairs of (j, k), where $j, k \in \{0, 1, \cdots, D_{\max}\}$.

Figure 1.11 Expected Migration Outcomes for Women with Brothers and without Brothers



Notes: This figure shows how the expected labor migration outcome varies by the local sex ratio for rural women with brothers and those without brothers, respectively. The histogram presents the distribution of the county-level sex ratios for the age cohort 16-20. The solid line shows that there is a strong and positive relationship between the local sex ratio and the propensity to migrate among rural women with brothers. On the other hand, the dash line shows that the migration decision of a rural woman without brothers appears to be uncorrelated with the local sex ratio. The expected work migration probability is estimated using the method of local polynomial smoothing.

Figure 1.12 Women with Brothers v.s. Women without Brothers (Split Sample)



	Model 1		Model 2		Model 3		Model 4		Model 5	
(s.e.)	(0.088)	(0.129)	(0.092)	(0.131)	(0.109)	(0.141)	(0.109)	(0.141)	(0.135)	(0.166)
p-value	[0.000]	[0.953]	[0.000]	[0.910]	[0.000]	[0.676]	[0.000]	[0.761]	[0.000]	[0.310]
Female controls	No		Yes		Yes		Yes		Yes	
Parent controls	No		No		Yes		Yes		Yes	
Household controls	No		No		No		Yes		Yes	
Local controls	No		No		No		No		Yes	
Provincial effects	Yes		Yes		Yes		Yes		Yes	

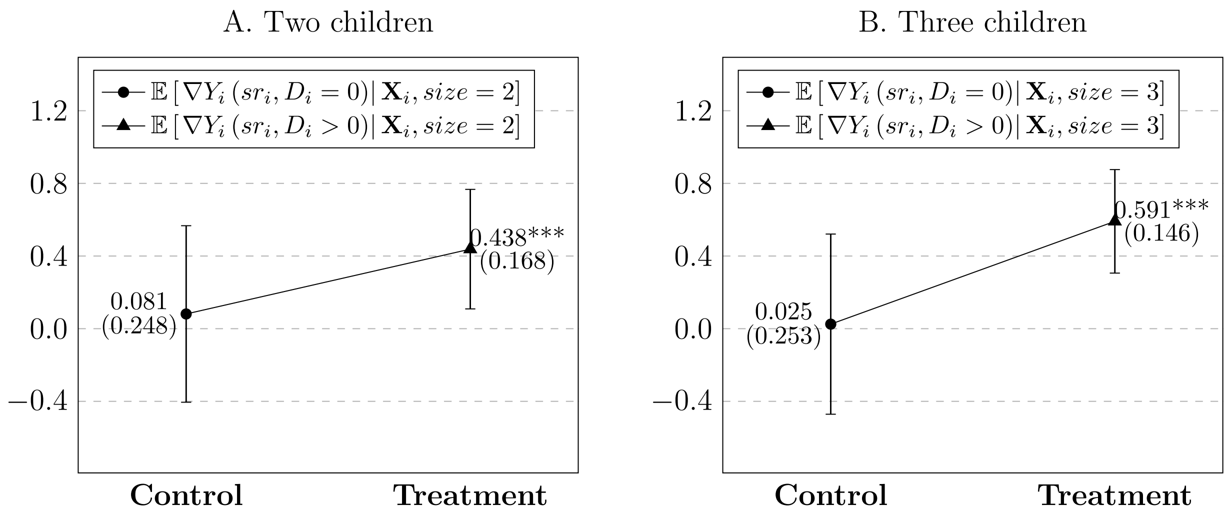
Notes: Robust standard errors in parentheses. This figure displays the marginal effects of the local sex ratio on the labor migration outcome for rural women with brothers and those without brothers, respectively. The parameters are obtained by separately estimating a probit model for the two types of rural women. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. The female controls are the personal characteristics of the rural woman, including years of schooling, age, a quadratic term of age, birth order, a Han ethnicity dummy and self-reported health. Parent controls include parental health conditions and parental education. Household controls include average family wealth and family size. Local controls include per capita GDP, per capita disposable income of rural households, the average wage in the urban sector, saving deposits by residents, loans in financial institutions and per capita number of firms in the local county. The provincial effects are captured by a set of provincial dummy variables.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

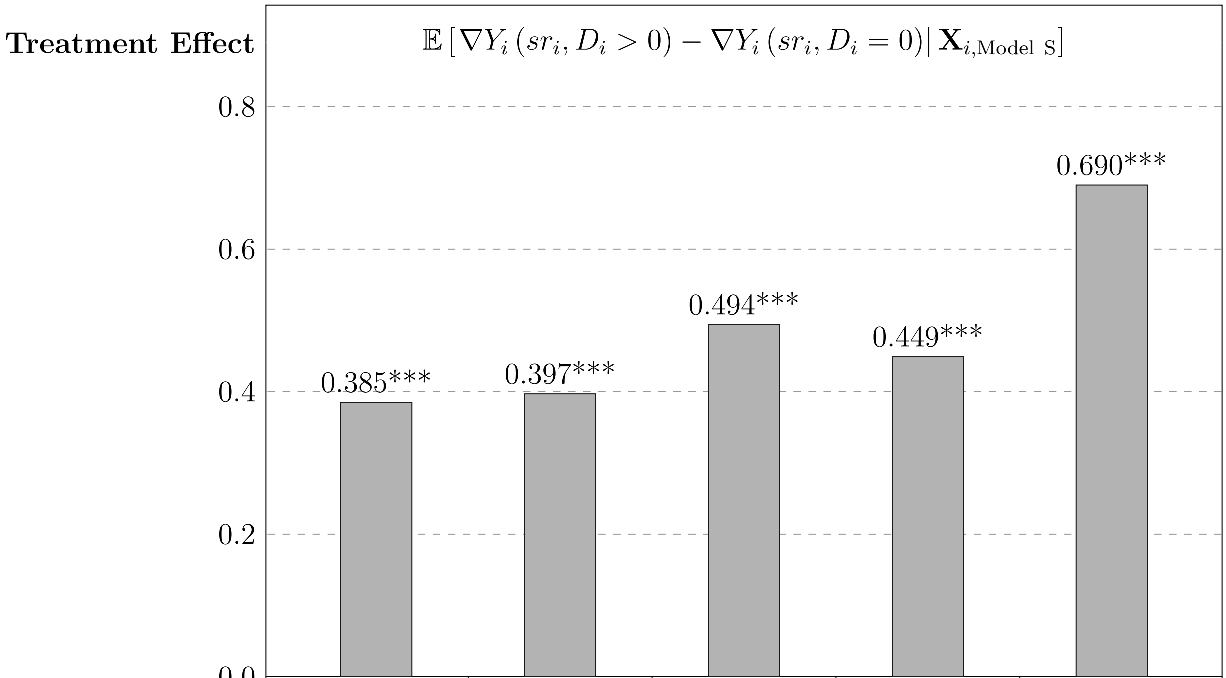
Figure 1.13 Fixing the Family Size (Split Sample)



Notes: Robust standard errors in parentheses. This figure shows the marginal effect of the local sex ratio on the labor migration outcome for rural women with brothers and those without brothers, respectively. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. The parameters are obtained by separately estimating a probit model for the two types of rural women. In Panel A, I restrict my sample to families with two children and Panel B focuses on those with three children. All estimates are conditional on the full set of controls.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 1.14 Women with Brothers v.s. Women without Brothers (Full Sample)

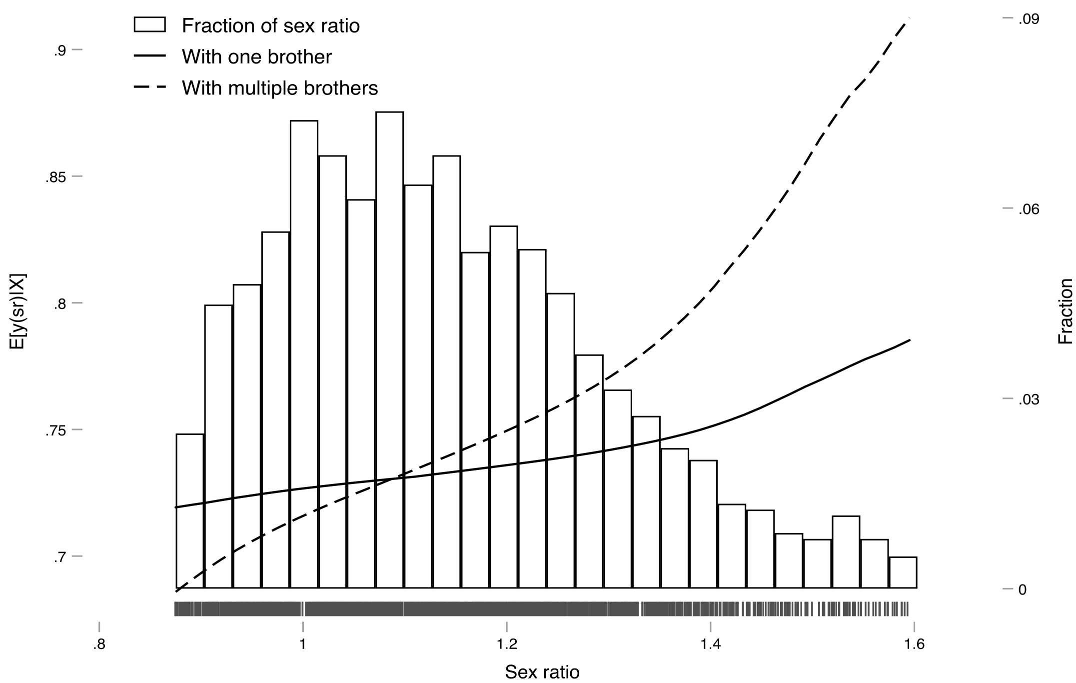


	Model 1	Model 2	Model 3	Model 4	Model 5
(s.e.)	(0.148)	(0.152)	(0.170)	(0.170)	(0.186)
p-value	0.009	0.009	0.004	0.008	0.000
Baseline	0.063	0.102	0.020	0.020	-0.100

Notes: Robust standard errors in parentheses. $D_i = 0$ represents the control group without brothers, and $D_i > 0$ represents the treated group with brothers. The baseline represents the group without brothers. This figure displays the estimated coefficient on the interaction term of the local sex ratio and an indicator for whether the rural woman has any brothers or not in a probit model for rural women's labor migration decision. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20.

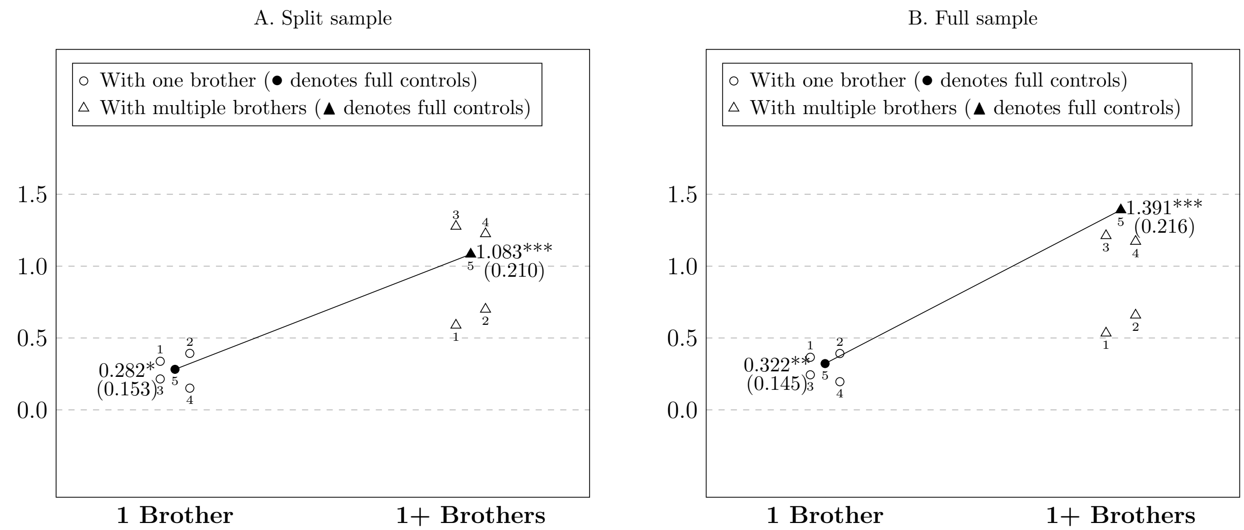
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 1.15 Expected Migration Outcomes for Women with One Brother and with Multiple Brothers



Notes: This figure shows how the expected labor migration outcome varies by the local sex ratio for rural women with one brother and those without multiple brothers, respectively. The histogram presents the distribution of the county-level sex ratios for the age cohort 16-20. As can be seen, for almost all local sex ratios, rural women with two or more brothers are much more likely to become a migrant worker than rural women with only one brother, and they responds more sensitively to changes in the sex ratio. The expected work migration probability is estimated using the method of local polynomial smoothing.

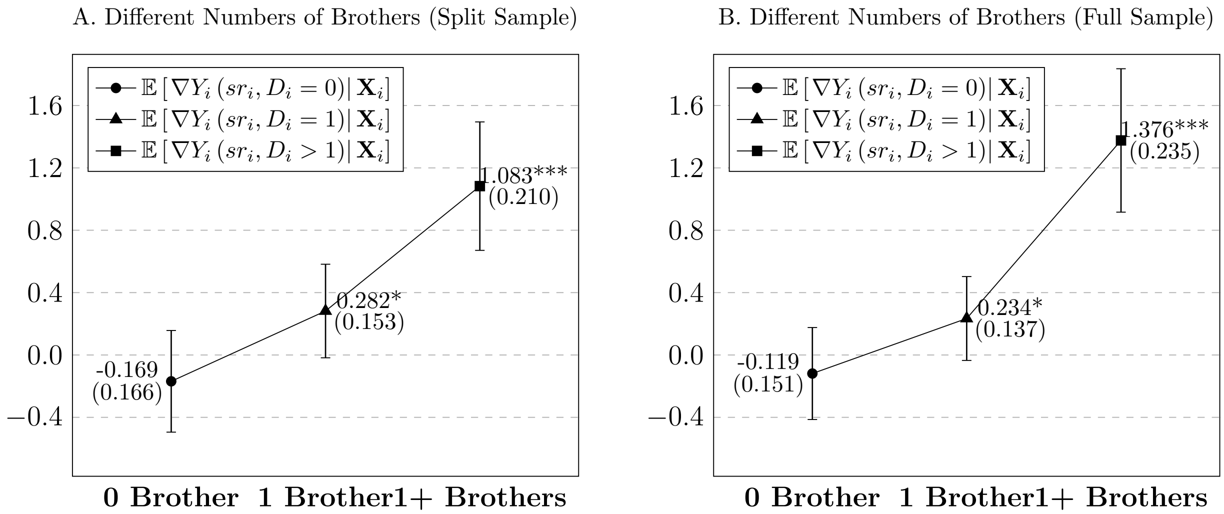
Figure 1.16 Women with One Brother v.s. Women with Multiple Brothers



Notes: Robust standard errors in parentheses. This figure displays the marginal effect of the local sex ratio on the labor migration outcome for rural women with one brother and those with multiple brothers, respectively. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. The parameters in Panel A are obtained by separately estimating a probit model for the two types of rural women. The parameters in Panel B are obtained by estimating a probit model with an interaction of the local sex ratio and an indicator for whether the rural women has two or more brothers (base group is those with only one brother). The numbers 1-5 represent Models 1-5.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 1.17 Treatment Effects on $\nabla Y_i\,(sr_i)$ of Different Sibling Structures



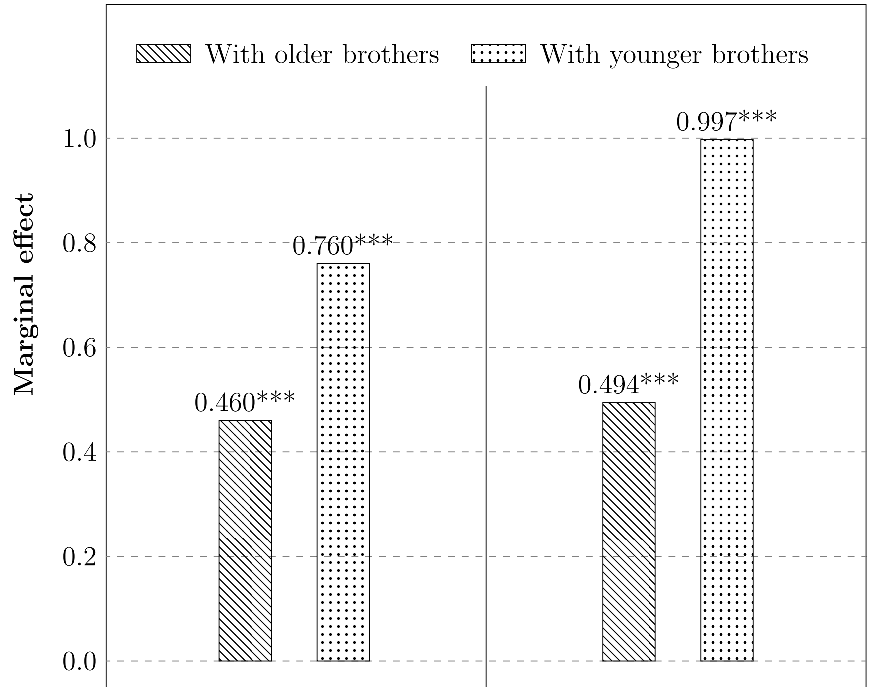
Notes: Robust standard errors in parentheses. This figure shows the marginal effect of the local sex ratio on the labor migration outcome for rural women without brothers, those with one brother and those with multiple brothers, respectively. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. The parameters in Panel A are obtained by separately estimating a probit model for the three types of rural women. The parameters in Panel B are obtained by estimating a probit model with interactions of the local sex ratio and the male sibling size dummies. All estimates are conditional on the full set of controls.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 1.18 Women with Older Brothers v.s. Women with Younger Brothers (Split Sample)



	Only older/younger		Average older/younger	
(s.e.)	(0.167)	(0.252)	(0.164)	(0.226)
p-value	[0.006]	[0.003]	[0.003]	[0.000]
Female controls	Yes		Yes	
Parent controls	Yes		Yes	
Household controls	Yes		Yes	
Local controls	Yes		Yes	
Provincial effects	Yes		Yes	

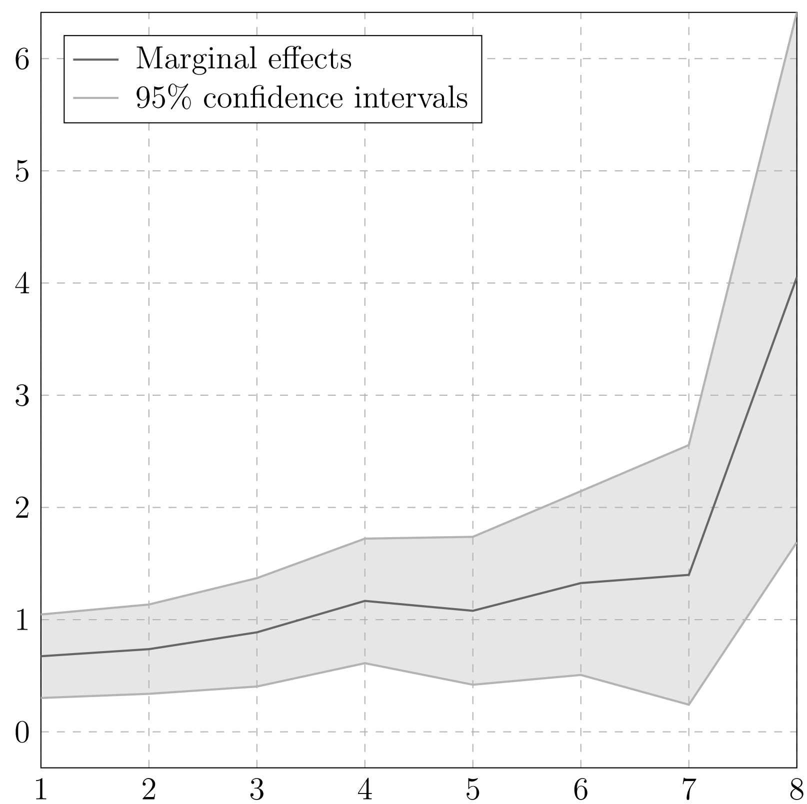
Notes: Robust standard errors in parentheses. This left panel displays the marginal effects of the local sex ratio on the labor migration outcome for rural women with only older brothers and those without only younger brothers, respectively. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. In the right panel, I compare rural women who are younger than the average age of their brothers and those who are older than the average age of their brothers. The parameters are obtained by separately estimating a probit model for the two types of rural women. The female controls are the personal characteristics of the rural woman, including years of schooling, age, a quadratic term of age, birth order, a Han ethnicity dummy and self-reported health. Parent controls include parental health conditions and parental education. Household controls include average family wealth and family size. Local controls include per capita GDP, per capita disposable income of rural households, the average wage in the urban sector, saving deposits by residents, loans in financial institutions and per capita number of firms in the local county. The provincial effects are captured by a set of provincial dummy variables.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

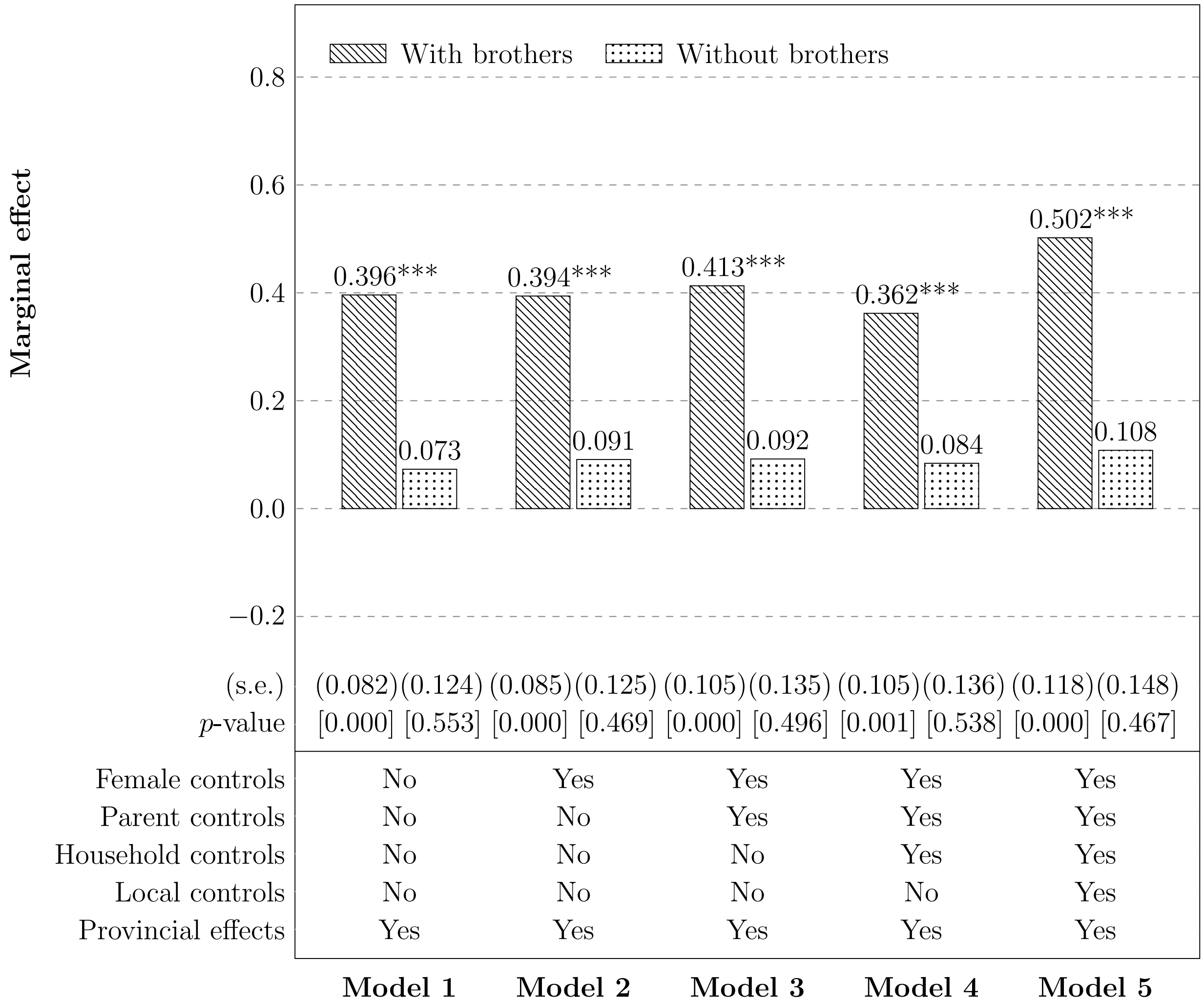
* Significant at the 10 percent level.

Figure 1.19 Marginal Effects for Different Age Gaps



Notes: This figure shows how the marginal effect of the local sex ratio on rural women's propensity to migrate changes with age gap when they have only younger brothers. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. The x-axis is the age gap between the rural woman and her youngest brother, and y-axis is the size of the marginal effect. I calculate the marginal effect for different age gaps using the pooled specification that augments the local sex ratio with the age gap dummies conditional on the full set of controls.

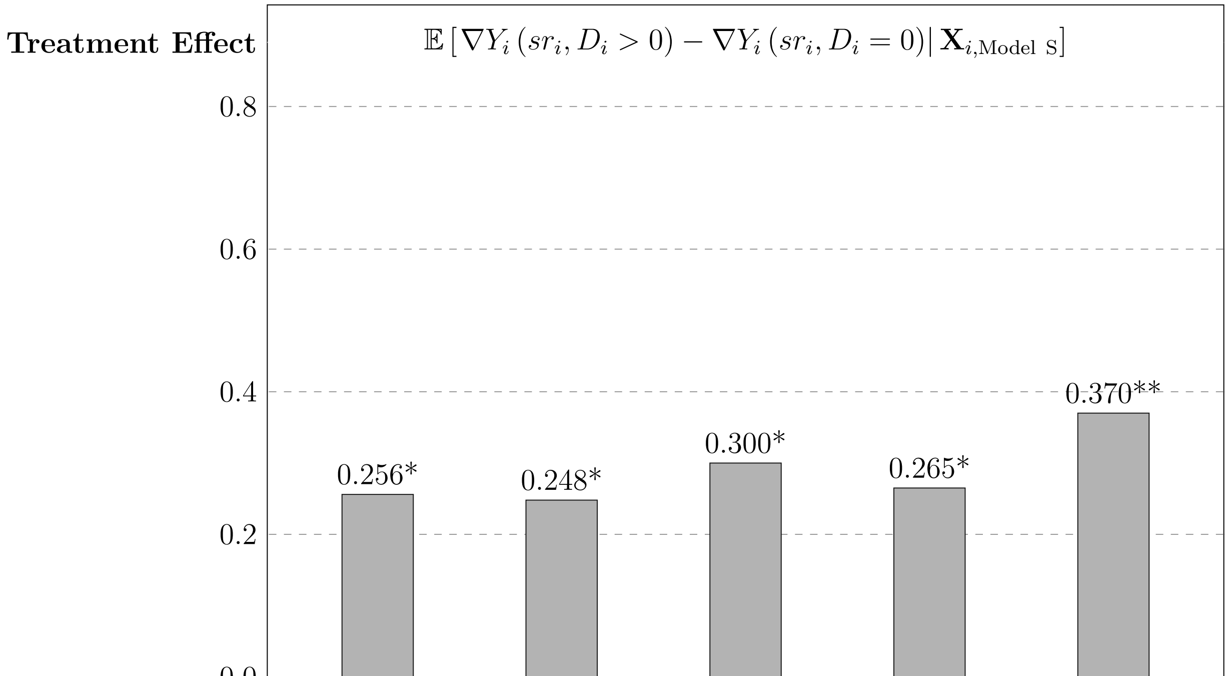
Figure 1.20 Women with Brothers v.s. Women without Brothers (Migration Experience, Split Sample)



Notes: Robust standard errors in parentheses. This figure displays the marginal effects of the local sex ratio on the labor migration experience (defined as an indicator for whether the rural woman has ever participated in migratory work) for rural women with brothers and those without brothers, respectively. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. The parameters are obtained by separately estimating a probit model for the two types of rural women. The female controls are the personal characteristics of the rural woman, including years of schooling, age, a quadratic term of age, birth order, a Han ethnicity dummy and self-reported health. Parent controls include parental health conditions and parental education. Household controls include average family wealth and family size. Local controls include per capita GDP, per capita disposable income of rural households, the average wage in the urban sector, saving deposits by residents, loans in financial institutions and per capita number of firms in the local county. The provincial effects are captured by a set of provincial dummy variables.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 1.21 Women with Brothers v.s. Women without Brothers (Migration Experience, Full Sample)



	Model 1	Model 2	Model 3	Model 4	Model 5
(s.e.)	(0.137)	(0.140)	(0.159)	(0.158)	(0.170)
p-value	0.062	0.076	0.059	0.094	0.030
Baseline	0.150	0.171	0.138	0.113	0.101

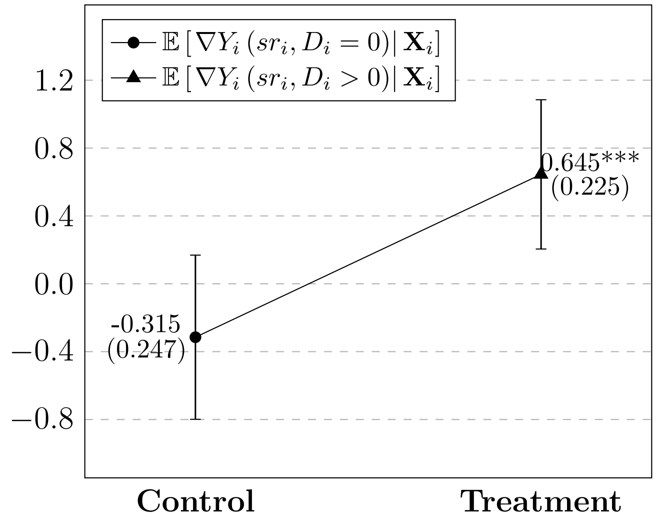
Notes: Robust standard errors in parentheses. $D_i = 0$ represents the control group without brothers, and $D_i > 0$ represents the treated group with brothers. The baseline represents the group without brothers. This figure displays the estimated coefficient on the interaction term of the local sex ratio and an indicator for whether the rural woman has any brothers or not in a probit model for rural women's labor migration experience (defined as an indicator for whether the rural woman has ever participated in migratory work). The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 1.22 Different Sex Ratio Measure: Age Cohort 16-25



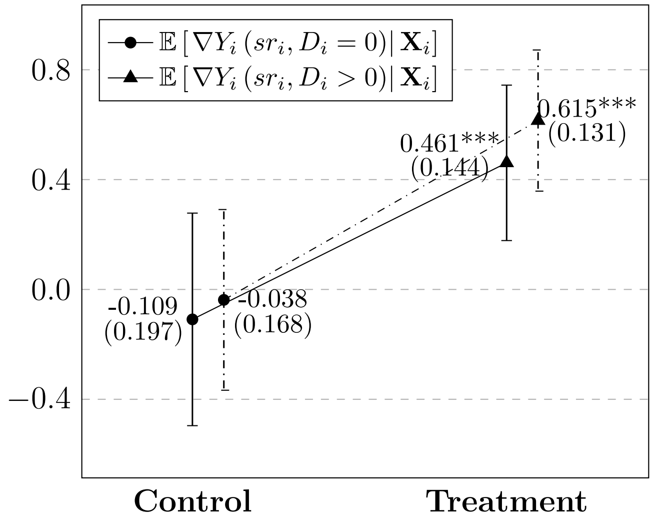
Notes: Robust standard errors in parentheses. $D_i = 0$ represents the control group without brothers, while $D_i > 0$ represents the treated group with brothers. This figure displays the marginal effect of the local sex ratio on the labor migration outcomes for rural women with brothers and those without brothers, respectively. The parameters are obtained by estimating a probit model with an interaction term of the local sex ratio and an indicator for whether the rural woman has any brothers or not. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-25. All estimates are conditional on the full set of controls.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 1.23 Younger Cohorts of Rural Women (Solid: Before Age 22; Dash: Before Age 25)



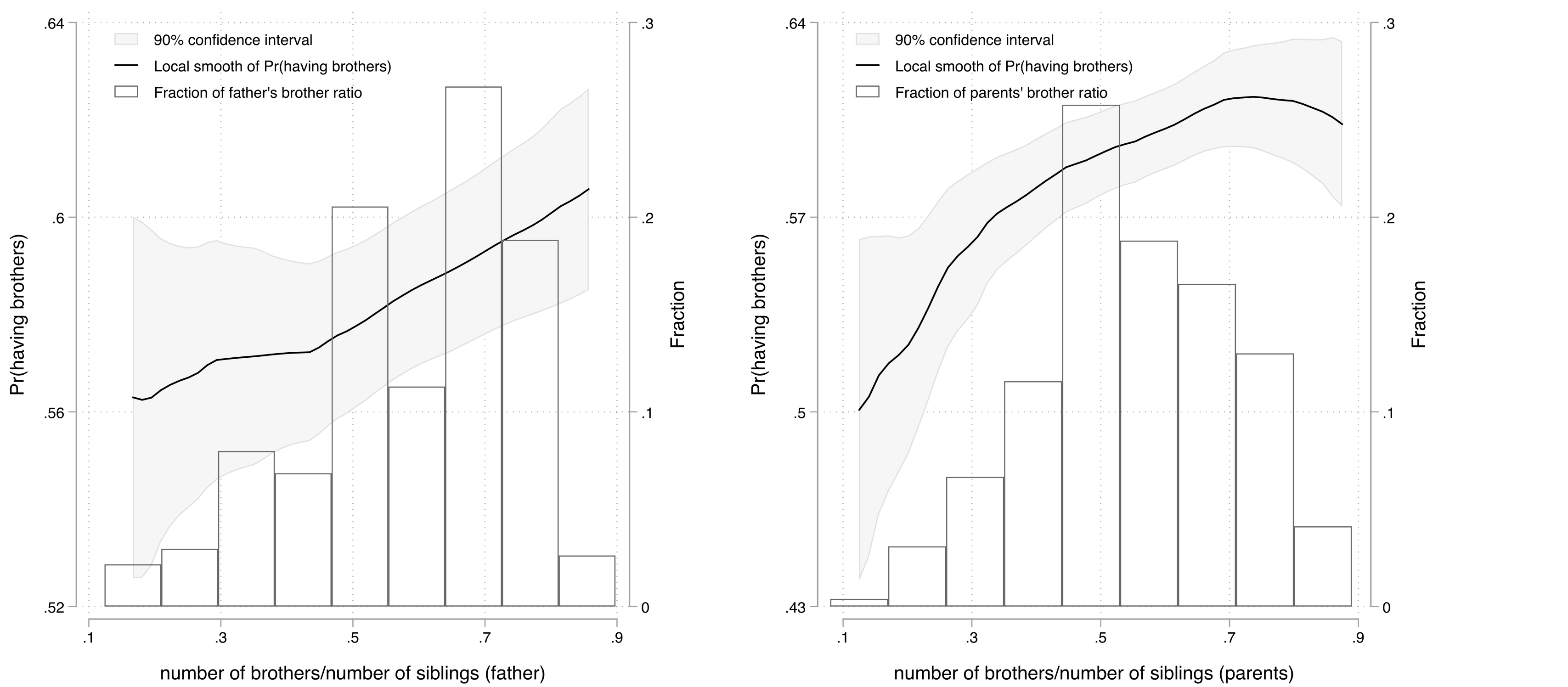
Notes: Robust standard errors in parentheses. $D_i = 0$ represents the control group without brothers, while $D_i > 0$ represents the treated group with brothers. This figure displays the marginal effect of the local sex ratio on the labor migration outcomes for rural women with brothers and those without brothers, respectively. The parameters are obtained by estimating a probit model with an interaction term of the local sex ratio and an indicator for whether the rural woman has any brothers or not. I restrict my sample to rural women younger than 22 (as shown by the solid line) and those younger than 25 (as shown by the dash line), respectively. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. All estimates are conditional on the full set of controls.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

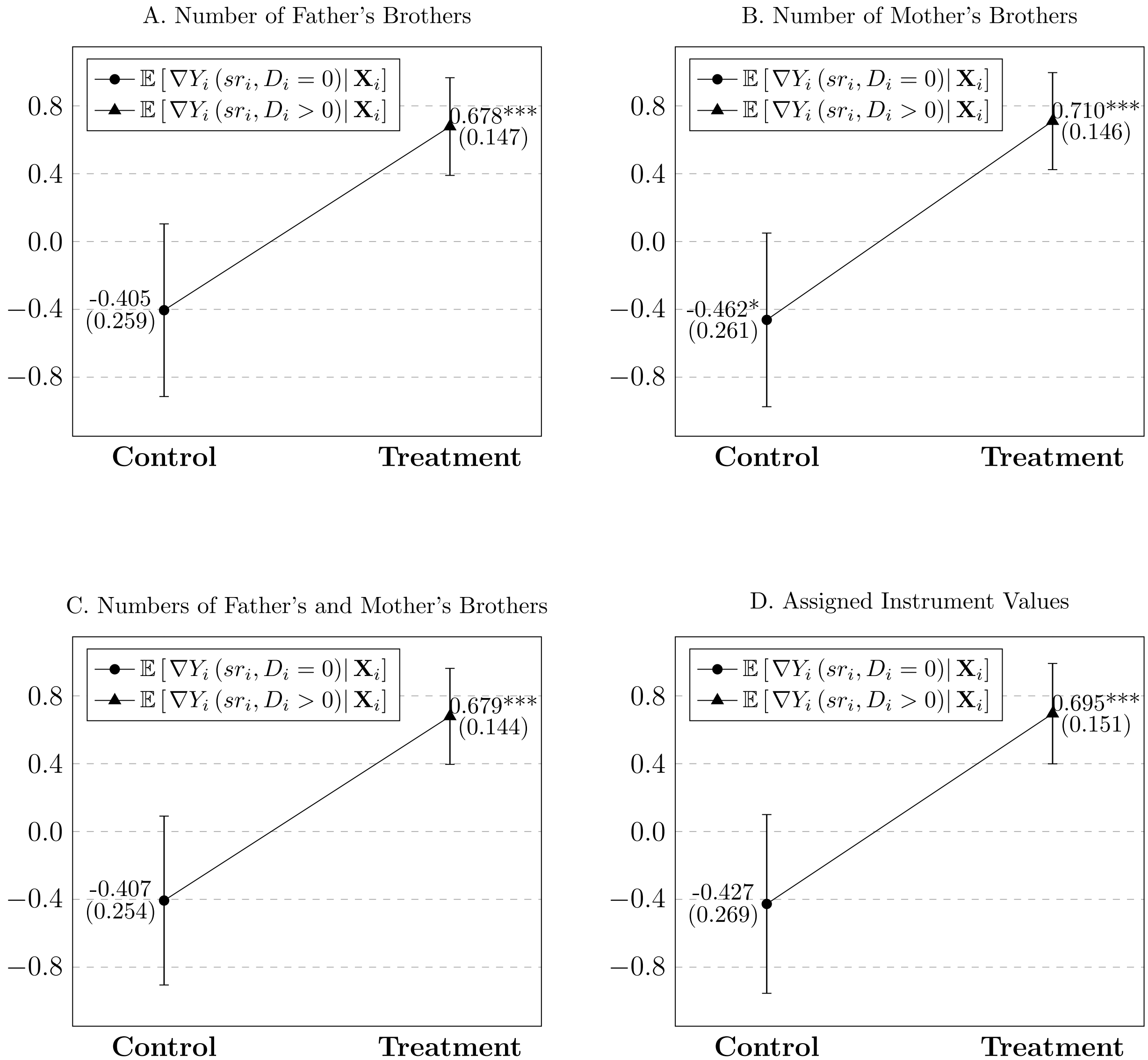
* Significant at the 10 percent level.

Figure 1.24 First Stage



Notes: This figure shows that whether a rural woman has brothers or not is positively correlated with the fraction of brothers in the total number of siblings that her parents ever have. The histograms displays the distributions of the corresponding male sibling proportions of the parents. The probability of having brothers is estimated using the method of local polynomial smoothing.

Figure 1.25 IV Estimation: Male Sibling Indicator



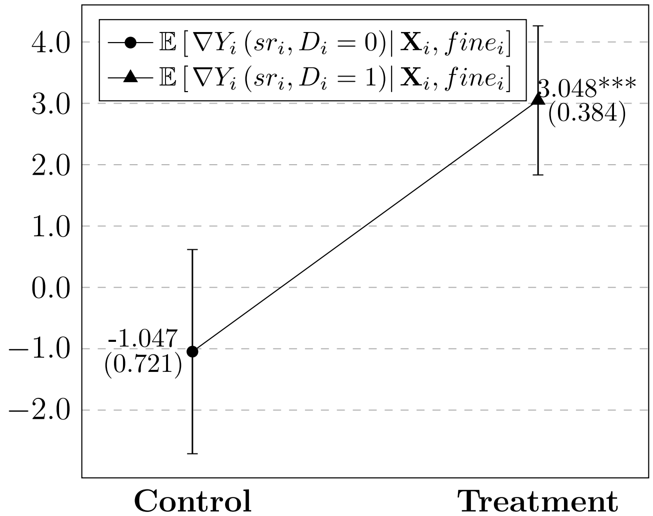
Notes: Robust standard errors in parentheses. This figure displays the marginal effect of the local sex ratio on the labor migration outcome for rural women with brothers and those without brothers, respectively. The parameters are obtained by estimating a probit model with an interaction term of the local sex ratio and an indicator for whether the rural woman has any brothers or not. I separately consider four possible instruments for the male sibling indicator: the number of the father's brothers Z_i^m, the number of the mother's brothers Z_i^f, the total number of the parents' brothers $Z_i^t = Z_i^m + Z_i^f$ and the instrument with assigned values Z_i. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. All estimates are conditional on the full set of controls and the corresponding total number of parental male siblings.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 1.26 IV Estimation: Local Sex Ratio



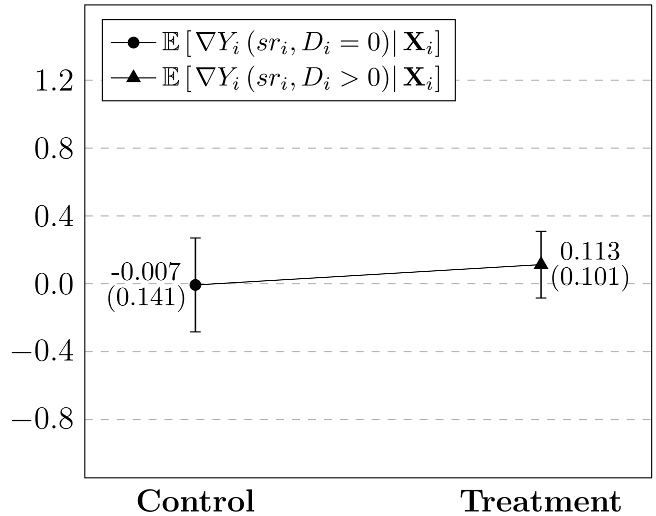
Notes: Robust standard errors in parentheses. This figure displays the marginal effect of the local sex ratio on the labor migration outcome for rural women with brothers and those without brothers, respectively. The parameters are obtained by estimating a probit model with an interaction term of the local sex ratio and an indicator for whether the rural woman has any brothers or not. The local sex ratio is instrumented with regional fertility fine rates. From a Wald test, I cannot reject the null hypothesis of no endogeneity at the 10% significant level. Hence, a standard probit model would be preferable. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. All estimates are conditional on the full set of controls and the corresponding total number of parental male siblings.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 1.27 Different Sex Ratio Measure: Age Cohort 65-70 (Full Sample)



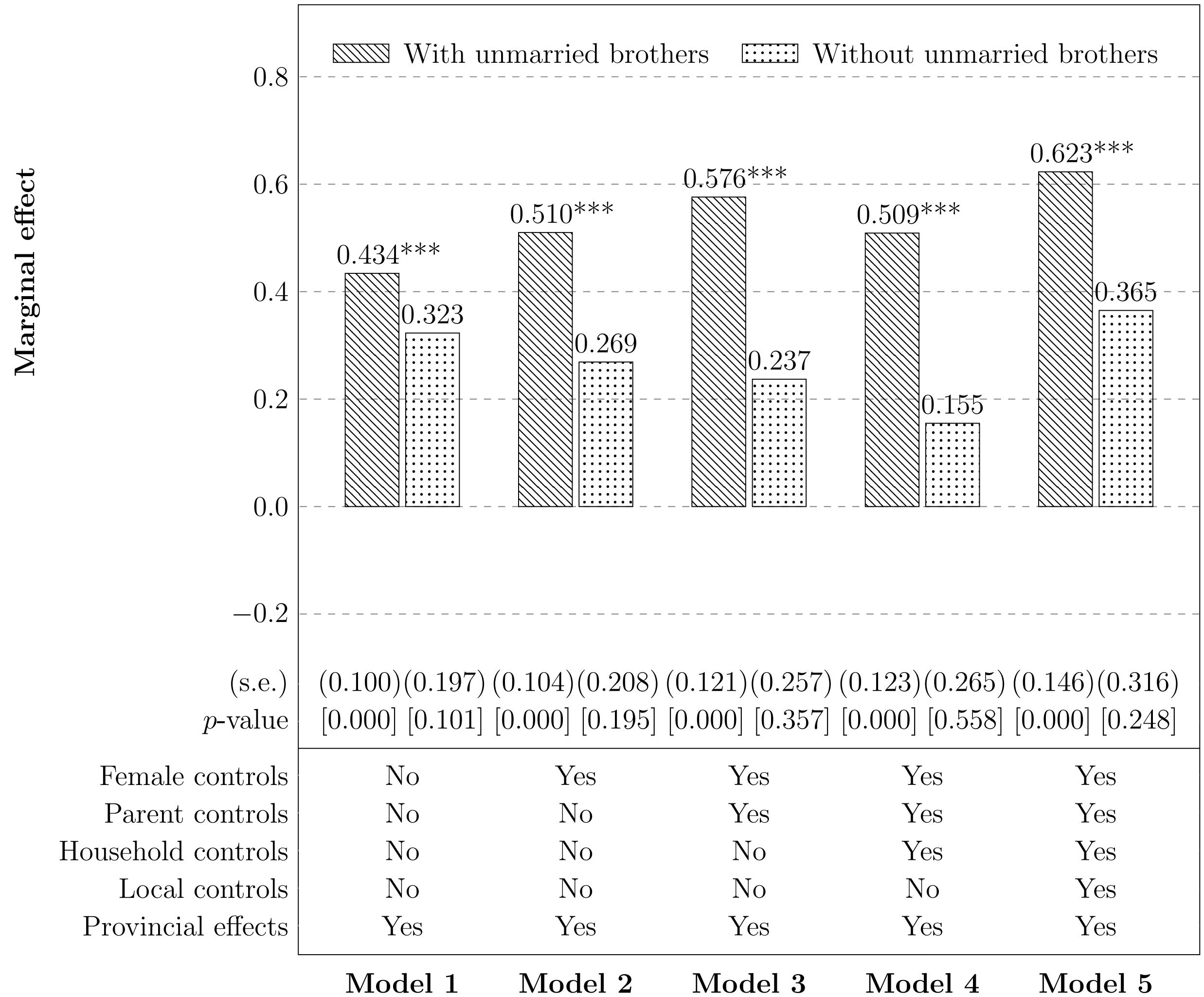
Notes: Robust standard errors in parentheses. $D_i = 0$ represents the control group without brothers, while $D_i > 0$ represents the treated group with brothers. This figure displays the marginal effect of the local sex ratio on the labor migration outcomes for rural women with brothers and those without brothers, respectively. The parameters are obtained by estimating a probit model with an interaction term of the local sex ratio and an indicator for whether the rural woman has any brothers or not. The local sex ratio is measured as the county-level sex ratio for the age cohort 65-70. All estimates are conditional on the full set of controls.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

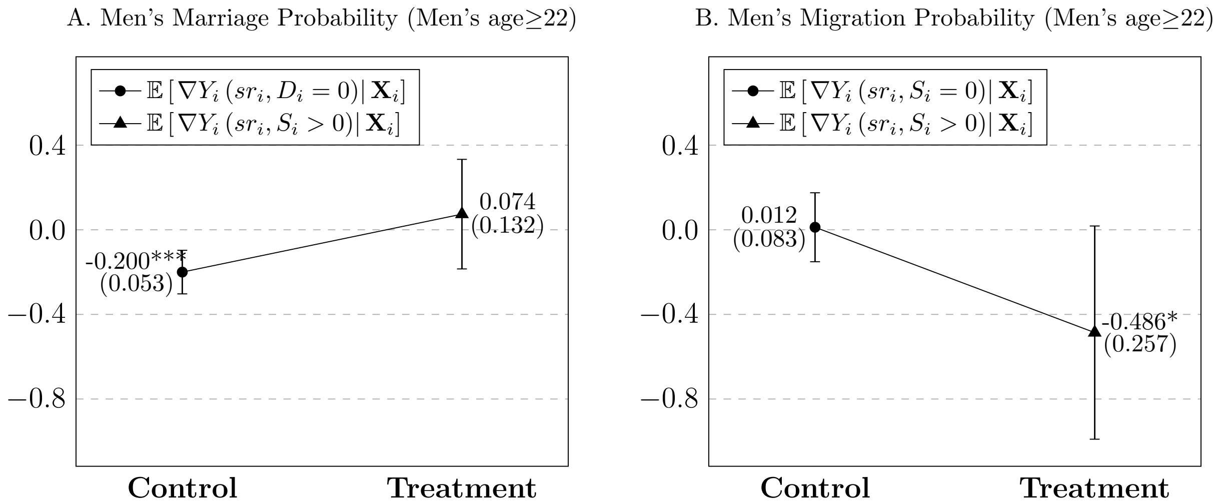
Figure 1.28 Women with Unmarried Brothers v.s. Women without Unmarried Brothers (Split Sample)



Notes: Robust standard errors in parentheses. This figure displays the marginal effects of the local sex ratio on the labor migration outcome for rural women with unmarried brothers and those with married brothers, respectively. The parameters are obtained by separately estimating a probit model for the two types of rural women. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. The female controls are the personal characteristics of the rural woman, including years of schooling, age, a quadratic term of age, birth order, a Han ethnicity dummy and self-reported health. Parent controls include parental health conditions and parental education. Household controls include average family wealth and family size. Local controls include per capita GDP, per capita disposable income of rural households, the average wage in the urban sector, saving deposits by residents, loans in financial institutions and per capita number of firms in the local county. The provincial effects are captured by a set of provincial dummy variables.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 1.29 Men with Migrant Sisters v.s. Men without Migrant Sisters (Full Sample)



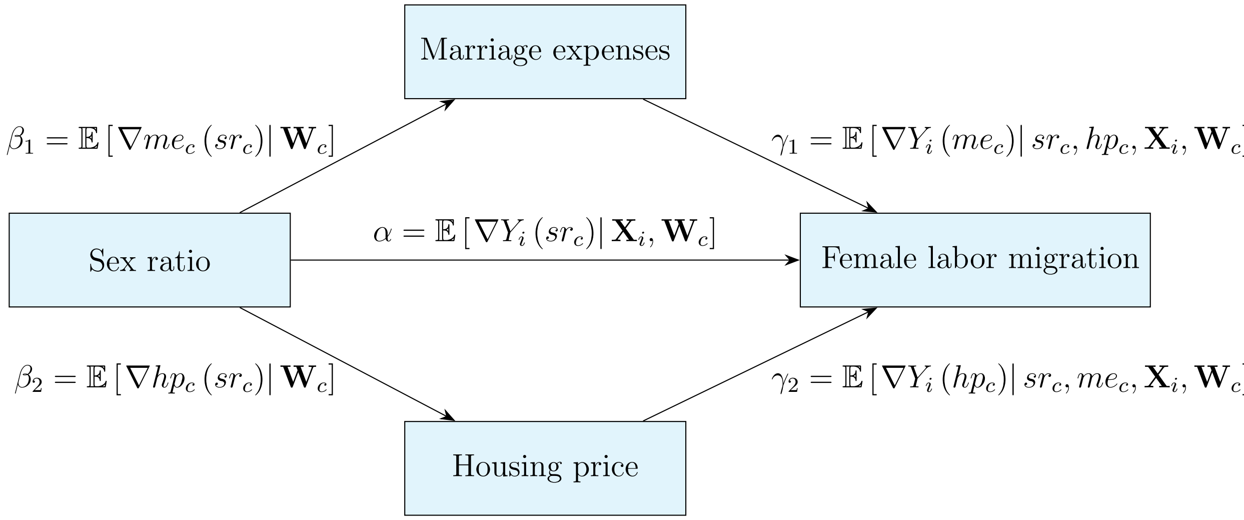
Notes: Robust standard errors in parentheses. $S_i = 0$ represents the group without migrant sisters, and $S_i > 0$ represent the group with migrant sisters. Panel A displays the marginal effect of the local sex ratio on the chance of being married for rural men with migrant sisters and those without migrant sisters, respectively. Panel B displays the marginal effect of the local sex ratio on the labor migration outcome for rural men with migrant sisters and those without migrant sisters, respectively. The parameters are obtained by estimating a probit model with an interaction term of the local sex ratio and an indicator for whether the rural man has any migrant sisters or not. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. I restrict the sample to rural men above 22, and control for a set of covariates that mirror those in the specification for rural women's labor migration decision.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

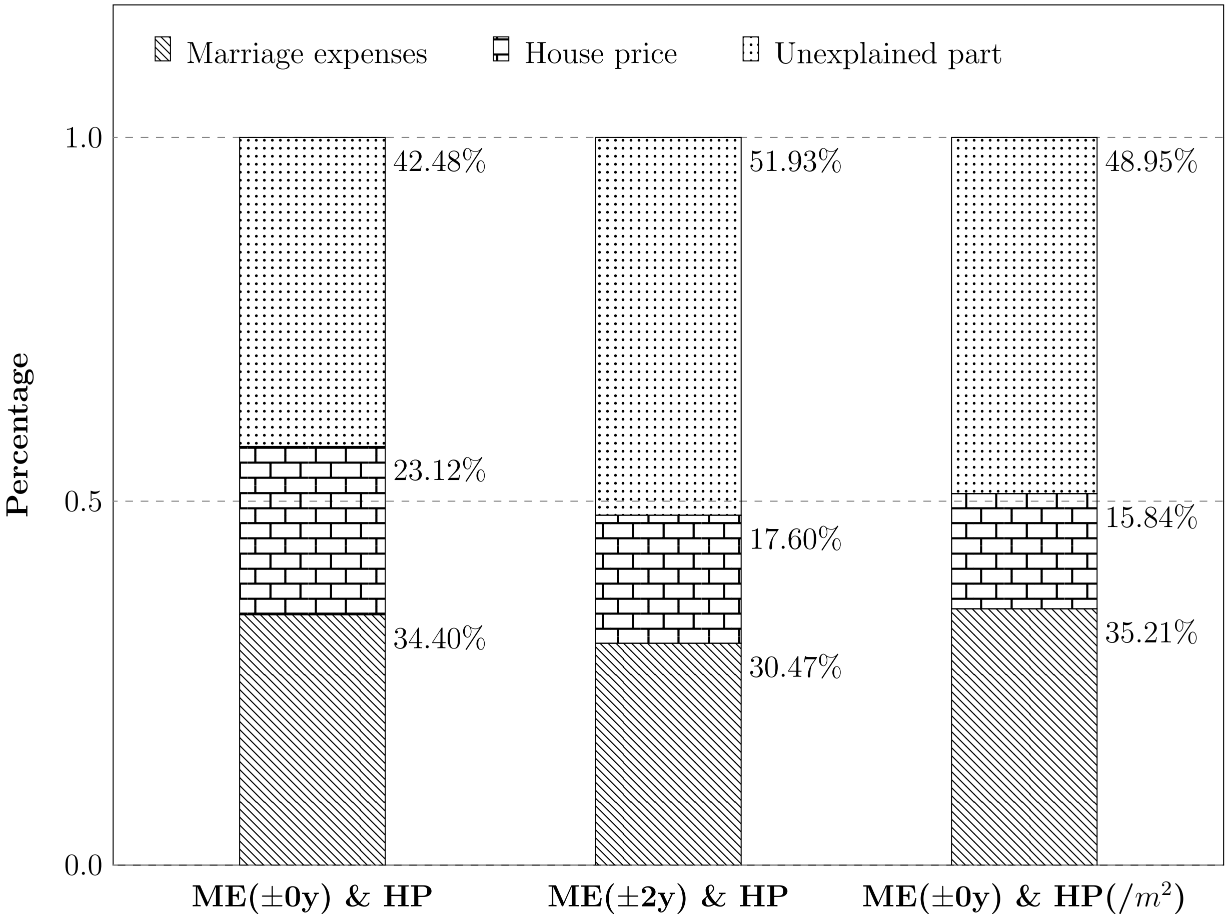
* Significant at the 10 percent level.

Figure 1.30 Mediation Analysis Design



Notes: Y_i is the migration status of rural woman i; me_c and hp_c denote the local marriage expenses and the local housing price, respectively; sr_c is the local sex ratio; X_i is a vector of variables for the rural woman's individual characteristics; W_c represents a series of controls capturing the local economic conditions.

Figure 1.31 Decomposition of the Local Sex Ratio Effect



Notes: "ME" represents "marriage expenses"; "HP" represents "house price"; "$\pm 2y$" means the variable is measured as a five-year average centered around the survey year. This figure displays the estimated decompositions of the local sex ratio effect on rural women's labor migration outcome. It is shown that 30.47-35.21% of the local sex ratio effect can be attributed to increases in marriage expenses and 15.84-23.12% of the local sex ratio effect can be accounted for by increases in housing price.

APPENDIX

1.A Proofs of Propositions in the Theoretical Model

Proof of Proposition 1.4.1: Consider the first order conditions of (h_m^1, z_f, z_d) in the three players' utilities, respectively. Since I assume that the Nash equilibrium is fully interior, I have

$$\begin{aligned}
h_m^1 &: \quad \frac{\beta\rho_1\alpha_m^\pi}{\beta h_m^1 + z_f + z_d} = \frac{\alpha_m^\ell}{1 - h_m^1 - h_m^2} \\
z_f &: \quad \frac{\alpha_f^c}{E_f + w_f h_f + (1-\gamma) w_d h_d - z_f} = \frac{\rho_1\alpha_f^\pi}{\beta h_m^1 + z_f + z_d} \\
z_d &: \quad \frac{\alpha_d^c}{E_d + \gamma w_d h_d - z_d} = \frac{\rho_1\alpha_d^\pi}{\beta h_m^1 + z_f + z_d}
\end{aligned}$$

$\Rightarrow$

$$\begin{aligned}
h_m^1 &= 1 - h_m^2 - \frac{\alpha_m^\ell \pi}{\beta\rho_1\alpha_m^\pi} \\
z_f &= E_f + w_f h_f + (1-\gamma) w_d h_d - \frac{\alpha_f^c \pi}{\rho_1\alpha_f^\pi} \\
z_d &= E_d + \gamma w_d h_d - \frac{\alpha_d^c \pi}{\rho_1\alpha_d^\pi}
\end{aligned}$$

Substituting these into $\pi = \beta h_m^1 + z_f + z_d$ yields

$$\pi\left(h_m^2, h_f, h_d\right) = \frac{\beta\left(1 - h_m^2\right) + w_f h_f + w_d h_d + E_f + E_d}{1 + \frac{\alpha_m^\ell}{\rho_1\alpha_m^\pi} + \frac{\alpha_f^c}{\rho_1\alpha_f^\pi} + \frac{\alpha_d^c}{\rho_1\alpha_d^\pi}}$$

The sufficient condition for $h_d = H_d$ to be an equilibrium is $u_d\left(h_d = H_d\right) > u_d\left(h_d = 0\right)$, i.e., $u_d\left(h_d = H_d\right) - u_d\left(h_d = 0\right) > 0$. Since

$$\begin{aligned}
u_d\left(h_d = H_d\right) &= \left(\alpha_d^c + \alpha_d^\pi\rho_1\right)\ln\pi\left(h_m^2, h_f, h_d = H_d\right) + \alpha_d^\ell\ln\left(1 - H_d\right) + \alpha_d^c\ln\left(\frac{\alpha_d^c}{\alpha_d^\pi\rho_1 p_d}\right) \\
u_d\left(h_d = 0\right) &= \left(\alpha_d^c + \alpha_d^\pi\rho_1\right)\ln\pi\left(h_m^2, h_f, h_d = 0\right) + \alpha_d^\ell\ln\left(1\right) + \alpha_d^c\ln\left(\frac{\alpha_d^c}{\alpha_d^\pi\rho_1 p_d}\right)
\end{aligned}$$

I have

$$\begin{aligned}
\Delta u_d(h_d) &= u_d(h_d = H_d) - u_d(h_d = 0) \\
&= (\alpha_d^c + \alpha_d^\pi \rho_1) \ln \frac{\beta(1-h_m^2) + w_f h_f + w_d H_d + E_f + E_d}{\beta(1-h_m^2) + w_f h_f + E_f + E_d} + \alpha_d^\ell \ln(1-H_d)
\end{aligned}$$

It is obvious that $\Delta u_d(h_d)$ is a monotonically increasing function of ρ_1. This property implies that the larger ρ_1, the higher the probability that event $\Delta u_d(h_d) > 0$ happens, i.e., the daughter prefers to participating in the labor market. Similarly, I also have

$$\begin{aligned}
\Delta u_f(h_f) &= u_f(h_f = H_f) - u_f(h_f = 0) \\
&= \left(\alpha_f^c + \alpha_f^\pi \rho_1\right) \ln \frac{\beta(1-h_m^2) + w_f H_f + w_d h_d + E_f + E_d}{\beta(1-h_m^2) + w_d h_d + E_f + E_d} + \alpha_f^\ell \ln(1-H_f)
\end{aligned}$$

and

$$\begin{aligned}
\Delta u_m\left(h_m^2\right) &= u_m\left(h_m^2 = H_m\right) - u_m\left(h_m^2 = 0\right) \\
&= \alpha_m^c \ln \frac{w_m H_m + E_m}{E_m} + \left(\alpha_m^\pi \rho_1 + \alpha_m^\ell\right) \ln \frac{\beta(1-H_m) + w_f h_f + w_d h_d + E_f + E_d}{\beta + w_f h_f + w_d h_d + E_f + E_d}
\end{aligned}$$

We can see that $\Delta u_f(h_f)$ and $\Delta u_m(h_m^2)$, respectively, are monotonically increasing and decreasing functions of ρ_1. Therefore, in equilibrium, an increase in the degree of son preference (ρ_1) increases the daughter's labor supply (h_d), increases the father's labor supply (h_f) while decreases the mother's labor supply (h_m^2). It is also easy to show that, in equilibrium, as the degree of son preference (ρ_1) increases, the family investment in the sons (I) as well as the well-being of the sons (π) will increase.

This completes the proof of Proposition 1.4.1. $\square$

Proof of Proposition 1.4.2: From $\Delta u_d(h_d)$ defined above, it is easy to show that $\partial \Delta u_d(h_d)/\partial w_f < 0$, $\partial \Delta u_d(h_d)/\partial h_f < 0$, $\partial \Delta u_d(h_d)/\partial E_d < 0$, and $\partial \Delta u_d(h_d)/\partial w_d > 0$. That is, in equilibrium, an increase in w_f, h_f or E_d makes the daughter less likely to work outside the home while an increase in w_d has the opposite effect. $\square$

Proof of Proposition 1.4.3: The proof is similar to that of Proposition 1.4.1. The main difference lies in the expression for the sons' well-being, which is derived as follows:

$$\pi\left(h_m^2, h_f, h_d\right) = \frac{\beta\left(1-h_m^2\right)+w_f h_f+w_d h_d+E_f+E_d-\rho_2 I_0}{1+\frac{\alpha_m^\ell}{\alpha_m^\pi}+\frac{\alpha_f^c}{\alpha_f^\pi}+\frac{\alpha_d^c}{\alpha_d^\pi}}$$

To guarantee that $h_d = H_d$ is an equilibrium, I should have $\Delta u_d\left(h_d\right) = u_d\left(h_d = H_d\right) - u_d\left(h_d = 0\right) > 0$, where

$$\begin{aligned}\Delta u_d\left(h_d\right) &= u_d\left(h_d = H_d\right) - u_d\left(h_d = 0\right)\\ &= \left(\alpha_d^c+\alpha_d^\pi\right)\ln\frac{\beta\left(1-h_m^2\right)+w_f h_f+w_d H_d+E_f+E_d-\rho_2 I_0}{\beta\left(1-h_m^2\right)+w_f h_f+E_f+E_d-\rho_2 I_0}+\alpha_d^\ell\ln\left(1-H_d\right)\end{aligned}$$

It can be shown that $\Delta u_d\left(h_d\right)$ is strictly increasing in ρ_2. Following the same argument as in the proof of Proposition 1.4.1, this implies that, as ρ_2 raises, the daughter will become more likely to participate in migratory work. Similarly, I also have

$$\begin{aligned}\Delta u_f\left(h_f\right) &= u_f\left(h_f = H_f\right) - u_f\left(h_f = 0\right)\\ &= \left(\alpha_f^c+\alpha_f^\pi\right)\ln\frac{\beta\left(1-h_m^2\right)+w_f H_f+w_d h_d+E_f+E_d-\rho_2 I_0}{\beta\left(1-h_m^2\right)+w_d h_d+E_f+E_d-\rho_2 I_0}+\alpha_f^\ell\ln\left(1-H_f\right)\end{aligned}$$

and

$$\begin{aligned}\Delta u_m\left(h_m^2\right) &= u_m\left(h_m^2 = H_m\right) - u_m\left(h_m^2 = 0\right)\\ &= \alpha_m^c\ln\frac{w_m H_m+E_m}{E_m}+\left(\alpha_m^\pi+\alpha_m^\ell\right)\ln\frac{\beta\left(1-H_m\right)+w_f h_f+w_d h_d+E_f+E_d-\rho_2 I_0}{\beta+w_f h_f+w_d h_d+E_f+E_d-\rho_2 I_0}\end{aligned}$$

One can easily see that $\Delta u_f\left(h_f\right)$ is strictly increasing in ρ_2 and $\Delta u_m\left(h_m^2\right)$ is strictly decreasing in ρ_2. It follows that, in equilibrium, an increase in the degree of marriage market pressure (ρ_2) increases the daughter's labor supply (h_d), increases the father's labor supply (h_f) while decreases the mother's labor supply (h_m^2). It is also straightforward to verify that, in equilibrium, as the degree of marriage market pressure (ρ_2) increases, the family investment in the sons ($I = \beta h_m^1 + z_f + z_d$) will increase, while the well-being of the sons (π) will decrease.

This completes the proof of Proposition 1.4.3. $\square$

1.B Extensions of the Theoretical Model

1.B.1 Daughter's Gain from the Marriage Market

In this appendix, I discuss two potential extensions to my analysis that allow for the daughter's gain from the marriage market. First, I consider the case where sex imbalance directly increases family wealth via a higher bride price. Then I introduce the daughter's welfare which enters into the household member's utility and depends positively on the sex ratio.

1.B.1.1 Increasing Family's Wealth

When the daughter's marital gain increases household wealth, the optimization problem can be written as follows:

$$\begin{aligned}
mother: &\max_{c_m, h_m^1, h_m^2} \alpha_m^c \ln c_m + \alpha_m^\pi \rho_1 \ln \pi + \alpha_m^\ell \ln\left(1 - h_m^1 - h_m^2\right) \\
&s.t.\ h_m^2 \in \{0, H_m\},\ 0 \le h_m^1, h_m^2 \le 1,\ h_m^1 + h_m^2 \le 1,\ p_m c_m \le E_m + w_m h_m^2 \\
father: &\max_{c_f, z_f, h_f} \alpha_f^c \ln c_f + \alpha_f^\pi \rho_1 \ln \pi + \alpha_f^\ell \ln(1 - h_f) \\
&s.t.\ h_f \in \{0, H_f\},\ 0 \le h_f \le 1,\ z_f + p_f c_f \le E_f + w_f h_f + (1-\gamma) w_d h_d + (1-\tilde{\gamma}) \rho_2 I_d \\
daughter: &\max_{c_d, z_d, h_d} \alpha_d^c \ln c_d + \alpha_d^\pi \rho_1 \ln \pi + \alpha_d^\ell \ln(1 - h_d) \\
&s.t.\ h_d \in \{0, H_d\},\ 0 \le h_d \le 1,\ z_d + p_d c_d \le E_d + \gamma w_d h_d + \tilde{\gamma} \rho_2 I_d
\end{aligned}$$

where $\pi = I - \rho_2 I_0 = \beta h_m^1 + z_f + z_d - \rho_2 I_0$ is the well-being of the sons, I_d denotes the minimum level of the daughter's gain from the marriage market in a sex balanced society and I assume that $I_d < I_0$, that is, the gain of having daughter is smaller than the expense of having son in the marriage market. This assumption is realistic as the housing cost, which comprises the majority of the marriage expenses in China, is typically much higher than the bride price payment and does not accrue to the bride's family. I assume that the father controls a fraction $(1-\tilde{\gamma})$ of the daughter's marriage gain while the daughter keeps the rest, where the parameters $\tilde{\gamma}$ satisfies $0 \leq \tilde{\gamma} \leq 1$.

Similarly, the sons' well-being takes the following form

$$\pi\left(h_m^2, h_f, h_d\right) = \frac{\beta\left(1-h_m^2\right)+w_f h_f + w_d h_d + E_f + E_d - \rho_2\left(I_0 - I_d\right)}{1+\frac{\alpha_m^\ell}{\alpha_m^\pi \rho_1}+\frac{\alpha_f^c}{\alpha_f^\pi \rho_1}+\frac{\alpha_d^c}{\alpha_d^\pi \rho_1}}$$

from which I can derive the optimal utility for the daughter by using the same logic as in Appendix 1.A. By comparing the utility conditional on $h_d = H_d$ to that conditional on $h_d = 0$, the daughter will work outside the home if and only if the following condition

$$\begin{aligned}
&\Delta u_d\left(h_d\right) = u_d\left(h_d = H_d\right) - u_d\left(h_d = 0\right) \\
&= \left(\alpha_d^c + \alpha_d^\pi \rho_1\right) \ln \frac{\beta\left(1-h_m^2\right)+w_f h_f + w_d H_d + E_f + E_d - \rho_2\left(I_0 - I_d\right)}{\beta\left(1-h_m^2\right)+w_f h_f + E_f + E_d - \rho_2\left(I_0 - I_d\right)} + \alpha_d^\ell \ln\left(1-H_d\right) > 0
\end{aligned}$$

is satisfied. It is obvious that $\Delta u_d\left(h_d\right)$ is a monotonically increasing function of both ρ_1 and ρ_2. Thus, including the daughter's marital gain as a part of family wealth does not alter my model predictions.

1.B.1.2 Increasing the Daughter's Well-Being and Parents also Care about the Daughter

In this extension, suppose the household members also derive utility from the daughter's well-being which is increasing in the degree of marriage market competition for brides[29].

[29] It is straightforward to extend to the setting where parents care about the daughter's consumption and leisure except for her gain from the marriage market. This extension would not alter the players' optimal behavior and lead to the same results as in my following discussion.

The optimization problem is characterized by:

$$
\begin{aligned}
mother: & \max_{c_m,h_m^1,\tilde{h}_m^1,h_m^2} \alpha_m^c \ln c_m + \alpha_m^\pi \left(\rho_1 \ln \pi + \ln \tilde{\pi}\right) + \alpha_m^\ell \ln \left(1 - h_m^1 - \tilde{h}_m^1 - h_m^2\right) \\
& s.t.\ h_m^2 \in \{0, H_m\},\ 0 \leq h_m^1, \tilde{h}_m^1, h_m^2 \leq 1,\ h_m^1 + \tilde{h}_m^1 + h_m^2 \leq 1,\ p_m c_m \leq E_m + w_m h_m^2 \\
father: & \max_{c_f,z_f,\tilde{z}_f,h_f} \alpha_f^c \ln c_f + \alpha_f^\pi \left(\rho_1 \ln \pi + \ln \tilde{\pi}\right) + \alpha_f^\ell \ln \left(1 - h_f\right) \\
& s.t.\ h_f \in \{0, H_f\},\ 0 \leq h_f \leq 1,\ z_f + \tilde{z}_f + p_f c_f \leq E_f + w_f h_f + (1-\gamma) w_d h_d \\
daughter: & \max_{c_d,z_d,\tilde{z}_d,h_d} \alpha_d^c \ln c_d + \alpha_d^\pi \left(\rho_1 \ln \pi + \ln \tilde{\pi}\right) + \alpha_d^\ell \ln \left(1 - h_d\right) \\
& s.t.\ h_d \in \{0, H_d\},\ 0 \leq h_d \leq 1,\ z_d + \tilde{z}_d + p_d c_d \leq E_d + \gamma w_d h_d
\end{aligned}
$$

where $\tilde{\pi} = \beta \tilde{h}_m^1 + \tilde{z}_f + \tilde{z}_d + \rho_2 I_d$ is the well-being of the daughter, $\tilde{h}_m^1$, $\tilde{z}_f$ and $\tilde{z}_d$ are the mother's labor contribution, the father's and her own monetary contributions, respectively. The main difference between the sons' and the daughter's welfare functions is that the sons need to pay the marriage expenses $\rho_2 I_0$ and the daughter receives the marriage benefits $\rho_2 I_d$, and I assume that $I_d < I_0$ as before. Using the same logic as in Appendix 1.A, π and $\tilde{\pi}$ satisfy $\pi = \rho_1 \tilde{\pi}$ in equilibrium, which take the following form

$$
\begin{cases}
\pi\left(h_m^2, h_f, h_d\right) = \dfrac{\beta\left(1-h_m^2\right)+w_f h_f+w_d h_d+E_f+E_d-\rho_2(I_0-I_d)}{1+\frac{1}{\rho_1}+\frac{\alpha_m^\ell}{\alpha_m^\pi \rho_1}+\frac{\alpha_f^c}{\alpha_f^\pi \rho_1}+\frac{\alpha_d^c}{\alpha_d^\pi \rho_1}} \\
\tilde{\pi}\left(h_m^2, h_f, h_d\right) = \dfrac{\beta\left(1-h_m^2\right)+w_f h_f+w_d h_d+E_f+E_d-\rho_2(I_0-I_d)}{1+\rho_1+\frac{\alpha_m^\ell}{\alpha_m^\pi}+\frac{\alpha_f^c}{\alpha_f^\pi}+\frac{\alpha_d^c}{\alpha_d^\pi}}
\end{cases}
$$

By comparing the utility conditional on $h_d = H_d$ to that conditional on $h_d = 0$, the daughter will work outside the home if and only if the following condition

$$
\begin{aligned}
&\Delta u_d\left(h_d\right) = u_d\left(h_d = H_d\right) - u_d\left(h_d = 0\right) \\
&= \left(\alpha_d^c + \alpha_d^\pi + \alpha_d^\pi \rho_1\right) \ln \frac{\beta\left(1-h_m^2\right) + w_f h_f + w_d H_d + E_f + E_d - \rho_2\left(I_0 - I_d\right)}{\beta\left(1-h_m^2\right) + w_f h_f + E_f + E_d - \rho_2\left(I_0 - I_d\right)} + \alpha_d^\ell \ln\left(1 - H_d\right) > 0
\end{aligned}
$$

is satisfied. Since $\Delta u_d\left(h_d\right)$ is a monotonically increasing function of both ρ_1 and ρ_2, this extension also gives the same results as my main analysis.

1.B.2 Continuous Labor Supply

I now relax the binary labor supply constraint, and assume that the players can choose the amount of working time. The optimization problems for the continuous case can be summarized as

$$\begin{aligned}
mother: \quad & \max_{c_m, h_m^1, h_m^2} \alpha_m^c \ln c_m + \alpha_m^\pi \rho_1 \ln \pi + \alpha_m^\ell \ln \left(1 - h_m^1 - h_m^2\right) \\
& s.t.\ \ 0 \leq h_m^1, h_m^2 \leq 1,\ h_m^1 + h_m^2 \leq 1,\ p_m c_m \leq w_m h_m^2 + (1-\kappa)(1-\gamma) w_d h_d \\
father: \quad & \max_{c_f, z_f, h_f} \alpha_f^c \ln c_f + \alpha_f^\pi \rho_1 \ln \pi + \alpha_f^\ell \ln (1 - h_f) \\
& s.t.\ \ 0 \leq h_f \leq 1,\ z_f + p_f c_f \leq w_f h_f + \kappa (1-\gamma) w_d h_d \\
daughter: \quad & \max_{c_d, z_d, h_d} \alpha_d^c \ln c_d + \alpha_d^\pi \rho_1 \ln \pi + \alpha_d^\ell \ln (1 - h_d) \\
& s.t.\ \ 0 \leq h_d \leq 1,\ z_d + p_d c_d \leq \gamma w_d h_d
\end{aligned}$$

where $\pi = I - \rho_2 I_0 = \beta h_m^1 + z_f + z_d - \rho_2 I_0$ is the well-being of the son and parameters γ, κ satisfy $0 \leq \gamma,\ \kappa \leq 1$. Note that I do not maintain the assumption that the three players each have unearned income since now labor supply is continuous. The effects on the Nash equilibrium of an increase in the degree of son preference or the intensity of marriage market competition are summarized in the following proposition.

Proposition 1.B.1. *Suppose the Nash equilibrium is fully interior. Then, in equilibrium, an increase in the degree of son preference (ρ_1) or the intensity of marriage market competition (ρ_2):*

- *Increases the daughter's labor supply (h_d).*
- *Increases the father's labor supply (h_f).*
- *Decreases the mother's labor supply (h_m^2).*
- *Increases the family investment in the sons (I).*
- *Increases (if it is ρ_1) or decreases (if it is ρ_2) the well-being of the sons (π).*
- *Increases the daughter's monetary contribution to the sons (z_d).*

- *Increases the father's monetary contribution to the sons (z_f).*

- *Increases the mother's labor contribution to the sons (h_m^1).*

Proof of Proposition 1.B.1: Consider the first order conditions of $(h_m^1, h_m^2, z_f, h_f, z_d, h_d)$ in the family members' utilities. By assumption, the Nash equilibrium is fully interior, thus the FOCs equal 0.

$$\begin{aligned}
h_m^1 &: \quad \frac{\beta\rho_1\alpha_m^\pi}{\beta h_m^1 + z_f + z_d - \rho_2 I_0} = \frac{\alpha_m^\ell}{1 - h_m^1 - h_m^2} \\
h_m^2 &: \quad \frac{\alpha_m^c w_m}{w_m h_m^2 + (1-\kappa)(1-\gamma) w_d h_d} = \frac{\alpha_m^\ell}{1 - h_m^1 - h_m^2} \\
z_f &: \quad \frac{\alpha_f^c}{w_f h_f + \kappa(1-\gamma) w_d h_d - z_f} = \frac{\rho_1\alpha_f^\pi}{\beta h_m^1 + z_f + z_d - \rho_2 I_0} \\
h_f &: \quad \frac{\alpha_f^c w_f}{w_f h_f + \kappa(1-\gamma) w_d h_d - z_f} = \frac{\alpha_f^\ell}{1 - h_f} \\
z_d &: \quad \frac{\alpha_d^c}{\gamma w_d h_d - z_d} = \frac{\rho_1\alpha_d^\pi}{\beta h_m^1 + z_f + z_d - \rho_2 I_0} \\
h_d &: \quad \frac{a\alpha_d^c w_d}{\gamma w_d h_d - z_d} = \frac{\alpha_d^\ell}{1 - h_d}
\end{aligned}$$

Solving these FOCs yields the reduced form solutions for the three players' labor supply:

$$\begin{aligned}
h_f &= 1 - \frac{\alpha_f^\ell}{\rho_1\alpha_f^\pi w_f}\left(\beta h_m^1 + z_f + z_d - \rho_2 I_0\right) \\
h_d &= 1 - \frac{\alpha_d^\ell}{\gamma\rho_1\alpha_d^\pi w_d}\left(\beta h_m^1 + z_f + z_d - \rho_2 I_0\right) \\
h_m^2 &= \left[\frac{\alpha_m^c}{\beta\rho_1\alpha_m^\pi} + \frac{(1-\kappa)(1-\gamma)\alpha_d^\ell}{\gamma\rho_1\alpha_d^\pi w_m}\right]\left(\beta h_m^1 + z_f + z_d - \rho_2 I_0\right) - \frac{(1-\kappa)(1-\gamma) w_d}{w_m}
\end{aligned}$$

from which the well-being of the sons and the parents' contribution satisfy

$$\begin{aligned}
\pi &= \beta h_m^1 + z_f + z_d - \rho_2 I_0 = \frac{\rho_1 \alpha_d^\pi}{1-\alpha_d^\pi}\left(\gamma w_d - z_d\right) \\
h_m^1 &= 1 - h_m^2 - \frac{\alpha_m^\ell}{\beta \rho_1 \alpha_m^\pi}\left(\beta h_m^1 + z_f + z_d - \rho_2 I_0\right) \\
&= 1 - \left[\frac{\left(1-\alpha_m^\pi\right)\alpha_d^\pi}{\beta \alpha_m^\pi \left(1-\alpha_d^\pi\right)} + \frac{\left(1-\kappa\right)\left(1-\gamma\right)\alpha_d^\ell}{\gamma w_m \left(1-\alpha_d^\pi\right)}\right]\left(\gamma w_d - z_d\right) + \frac{\left(1-\kappa\right)\left(1-\gamma\right) w_d}{w_m} \\
z_f &= w_f h_f + \kappa\left(1-\gamma\right) w_d h_d - \frac{\alpha_f^c}{\rho_1 \alpha_f^\pi}\left(\beta h_m^1 + z_f + z_d - \rho_2 I_0\right) \\
&= w_f + \kappa\left(1-\gamma\right) w_d - \left[\frac{\left(1-\alpha_f^\pi\right)\alpha_d^\pi}{\alpha_f^\pi\left(1-\alpha_d^\pi\right)} + \frac{\kappa\left(1-\gamma\right)\alpha_d^\ell}{\gamma\left(1-\alpha_d^\pi\right)}\right]\left(\gamma w_d - z_d\right)
\end{aligned}$$

Then, substitute h_m^1 and z_f into π, I have

$$\begin{aligned}
\pi =& \frac{\rho_1 \alpha_d^\pi}{1-\alpha_d^\pi}\left(\gamma w_d - z_d\right) \\
=& \left\{ w_f + \kappa\left(1-\gamma\right) w_d - \left[\frac{\left(1-\alpha_f^\pi\right)\alpha_d^\pi}{\alpha_f^\pi\left(1-\alpha_d^\pi\right)} + \frac{\kappa\left(1-\gamma\right)\alpha_d^\ell}{\gamma\left(1-\alpha_d^\pi\right)}\right]\left(\gamma w_d - z_d\right)\right\} + z_d + \\
& \left\{\beta - \left[\frac{\left(1-\alpha_m^\pi\right)\alpha_d^\pi}{\alpha_m^\pi\left(1-\alpha_d^\pi\right)} + \frac{\left(1-\kappa\right)\left(1-\gamma\right)\beta\alpha_d^\ell}{\gamma w_m\left(1-\alpha_d^\pi\right)}\right]\left(\gamma w_d - z_d\right) + \frac{\left(1-\kappa\right)\left(1-\gamma\right)\beta w_d}{w_m}\right\} - \rho_2 I_0
\end{aligned}$$

from which I can rewrite z_d as:

$$z_d = \gamma w_d - \frac{\gamma \alpha_f^\pi \alpha_m^\pi \left(1-\alpha_d^\pi\right) w_m \left(\beta + w_f + \gamma w_d - \rho_2 I_0\right) + \gamma\left(1-\alpha_d^\pi\right) w_d K_2}{K_1 + \gamma \rho_1 \alpha_f^\pi \alpha_m^\pi \alpha_d^\pi w_m + \alpha_d^\ell K_2}$$

where

$$\begin{cases}
K_1 = \gamma\left[\alpha_f^\pi \alpha_m^\pi\left(1-\alpha_d^\pi\right) + \alpha_f^\pi\left(1-\alpha_m^\pi\right)\alpha_d^\pi + \left(1-\alpha_f^\pi\right)\alpha_m^\pi\alpha_d^\pi\right] w_m \\
K_2 = \left(1-\gamma\right)\left[\left(1-\kappa\right)\beta + \kappa w_m\right]\alpha_f^\pi \alpha_m^\pi
\end{cases}.$$

The first order derivatives of z_d with respect to (ρ_1, ρ_2) are thus given by

$$\begin{aligned}
\frac{dz_d}{d\rho_1} &= \frac{\left[\gamma \alpha_f^\pi \alpha_m^\pi \left(1-\alpha_d^\pi\right) w_m \left(\beta + w_f + \gamma w_d - \rho_2 I_0\right) + \gamma\left(1-\alpha_d^\pi\right) w_d K_2\right]\cdot \gamma \alpha_f^\pi \alpha_m^\pi \alpha_d^\pi w_m}{\left(K_1 + \gamma \rho_1 \alpha_f^\pi \alpha_m^\pi \alpha_d^\pi w_m + \alpha_d^\ell K_2\right)^2} > 0 \\
\frac{dz_d}{d\rho_2} &= \frac{\gamma \alpha_f^\pi \alpha_m^\pi \left(1-\alpha_d^\pi\right) w_m I_0}{K_1 + \gamma \rho_1 \alpha_f^\pi \alpha_m^\pi \alpha_d^\pi w_m + \alpha_d^\ell K_2} > 0
\end{aligned}$$

Similarly, I can solve the first order derivatives of $(h_m^1, h_m^2, z_f, h_f, h_d, \pi, I)$ with respect to (ρ_1, ρ_2):

$$
\begin{aligned}
\frac{dz_f}{d\rho_j} &= \left[\frac{\left(1-\alpha_f^\pi\right)\alpha_d^\pi}{\alpha_f^\pi\left(1-\alpha_d^\pi\right)} + \frac{\kappa\left(1-\gamma\right)\alpha_d^\ell}{\gamma\left(1-\alpha_d^\pi\right)}\right] \cdot \frac{dz_d}{d\rho_j} > 0 \\
\frac{dh_m^1}{d\rho_j} &= \left[\frac{\left(1-\alpha_m^\pi\right)\alpha_d^\pi}{\beta\alpha_m^\pi\left(1-\alpha_d^\pi\right)} + \frac{\left(1-\kappa\right)\left(1-\gamma\right)\alpha_d^\ell}{\gamma w_m\left(1-\alpha_d^\pi\right)}\right] \cdot \frac{dz_d}{d\rho_j} > 0 \\
\frac{dI}{d\rho_j} &= \beta \cdot \frac{dh_m^1}{d\rho_j} + \frac{dz_f}{d\rho_j} + \frac{dz_d}{d\rho_j} > 0 \\
\frac{dz}{d\rho_j} &= \begin{cases} \beta \cdot \frac{dh_m^1}{d\rho_j} + \frac{dz_f}{d\rho_j} + \frac{dz_d}{d\rho_j} > 0\,, & j=1 \\ -\frac{\rho_1\alpha_d^\pi}{1-\alpha_d^\pi} \cdot \frac{dz_d}{d\rho_j} < 0\,, & j=2 \end{cases} \\
\frac{dh_f}{d\rho_j} &= \frac{\alpha_f^\ell\alpha_d^\pi}{\alpha_f^\pi w_f\left(1-\alpha_d^\pi\right)} \cdot \frac{dz_d}{d\rho_j} > 0 \\
\frac{dh_d}{d\rho_j} &= \frac{\alpha_d^\ell}{\gamma w_d\left(1-\alpha_d^\pi\right)} \cdot \frac{dz_d}{d\rho_j} > 0 \\
\frac{dh_m^2}{d\rho_j} &= -\left[\frac{\alpha_m^c\alpha_d^\pi}{\beta\alpha_m^\pi\left(1-\alpha_d^\pi\right)} + \frac{\left(1-\kappa\right)\left(1-\gamma\right)\alpha_d^\ell}{\gamma w_m\left(1-\alpha_d^\pi\right)}\right] \cdot \frac{dz_d}{d\rho_j} < 0
\end{aligned}
$$

where $j = 1, 2$. This completes the proof of Proposition 1.B.1. □

1.C Proofs of Propositions in the Conceptual Framework

Proof of Proposition 1.6.1: To prove this proposition, note that under Assumption 1.6.1,

$$
\begin{aligned}
& \nabla_{sr}\mathbb{E}\left[\tau_i\left(sr, \mathbf{X}_i\right)\middle| sr, D_i, \mathbf{X}_i\right] \\
=& \int_{\mathbb{R}_u} \left[\nabla_{sr}\tau_i\left(sr, \mathbf{X}_i\right) f\left(u_i\middle| sr, D_i, \mathbf{X}_i\right) + \tau_i\left(sr, \mathbf{X}_i\right)\nabla_{sr} f\left(u_i\middle| sr, D_i, \mathbf{X}_i\right)\right] du_i \\
=& \mathbb{E}\left[\nabla_{sr}\tau_i\left(sr, \mathbf{X}_i\right)\middle| sr, D_i, \mathbf{X}_i\right].
\end{aligned}
$$

Then, I have

$$
\psi_{ace}\left(\mathbf{X}_i\right) = \int_{\mathbb{R}_u} \nabla_{sr}\tau_i\left(sr, \mathbf{X}_i\right) f\left(u_i\middle| sr, D_i, \mathbf{X}_i\right) du_i = \nabla_{sr}\mathbb{E}\left[\tau_i\left(sr, \mathbf{X}_i\right)\middle| sr, D_i, \mathbf{X}_i\right] = \nabla_{sr}\tau\left(sr, \mathbf{X}_i\right).
$$

This completes the proof of Proposition 1.6.1. □

Proof of Proposition 1.6.2: Note that $\mathbb{E}\left[\mathbf{1}\left\{D_i = j\right\}\middle|\, \mathbf{X}_i\right] = \Pr\left[D_i = j\middle|\, \mathbf{X}_i\right] = p^j\left(\mathbf{X}_i\right)$ and

$$\begin{aligned}
\mathbb{E}\left[p^j\left(\mathbf{X}_i\right)^{-1}\mathbf{1}\left\{D_i = j\right\}Y_i\left(sr, \mathbf{X}_i\right)\middle|\, \mathbf{X}_i\right] &= \mathbb{E}\left\{p^j\left(\mathbf{X}_i\right)^{-1}\mathbf{1}\left\{D_i = j\right\}\mathbb{E}\left[Y_i^j\left(sr, \mathbf{X}_i\right)\middle|\, \mathbf{X}_i, D_i\right]\middle|\, \mathbf{X}_i\right\} \\
&= \mathbb{E}\left\{p^j\left(\mathbf{X}_i\right)^{-1}\mathbf{1}\left\{D_i = j\right\}\mathbb{E}\left[Y_i^j\left(sr, \mathbf{X}_i\right)\middle|\, \mathbf{X}_i\right]\middle|\, \mathbf{X}_i\right\} \\
&= \mathbb{E}\left[Y_i^j\left(sr, \mathbf{X}_i\right)\middle|\, \mathbf{X}_i\right].
\end{aligned}$$

Here the second line uses the conditional independence assumption in Assumption 1.6.2. Hence, I have

$$\begin{aligned}
\tau_{ate}^{j,k}\left(sr, \mathbf{X}_i\right) &= \mathbb{E}\left[Y_i^j\left(sr, \mathbf{X}_i\right) - Y_i^k\left(sr, \mathbf{X}_i\right)\middle|\, \mathbf{X}_i\right] \\
&= \mathbb{E}\left[\left(\frac{\mathbf{1}\left\{D_i = j\right\}}{p^j\left(\mathbf{X}_i\right)} - \frac{\mathbf{1}\left\{D_i = k\right\}}{p^k\left(\mathbf{X}_i\right)}\right)Y_i\left(sr, \mathbf{X}_i\right)\middle|\, \mathbf{X}_i\right].
\end{aligned}$$

This completes the proof of Proposition 1.6.2. □

Proof of Proposition 1.6.3: Note that

$$\begin{aligned}
\tau_{ate}\left(sr, \mathbf{X}_i\right) &= \sum_{j=1}^{D_{\max}} w^j\left(\mathbf{X}_i\right)\tau_{ate}^{j,0}\left(sr, \mathbf{X}_i\right) \\
&= \sum_{j=1}^{D_{\max}} w^j\left(\mathbf{X}_i\right)\mathbb{E}\left[Y_i^j\left(sr, \mathbf{X}_i\right) - Y_i^0\left(sr, \mathbf{X}_i\right)\middle|\, \mathbf{X}_i\right] \\
&= \mathbb{E}\left[\sum_{j=1}^{D_{\max}} w^j\left(\mathbf{X}_i\right)Y_i^j\left(sr, \mathbf{X}_i\right) - Y_i^0\left(sr, \mathbf{X}_i\right)\middle|\, \mathbf{X}_i\right].
\end{aligned}$$

Here the third line uses $\sum_{j=1}^{D_{\max}} w^j\left(\mathbf{X}_i\right) = 1$ and the last line comes from the law of iterated expectations.

To identify the weighted average treatment effect $\tau_{ate}\left(sr, \mathbf{X}_i\right)$, I use the result from Proposition 1.6.2 and obtain

$$
\begin{aligned}
\tau_{ate}(sr, \mathbf{X}_i) &= \sum_{j=1}^{D_{\max}} w^j(\mathbf{X}_i)\, \tau_{ate}^{j,0}(sr, \mathbf{X}_i) \\
&= \mathbb{E}\left[\sum_{j=1}^{D_{\max}} w^j(\mathbf{X}_i) \left(\frac{\mathbf{1}\{D_i = j\}}{p^j(\mathbf{X}_i)} - \frac{\mathbf{1}\{D_i = 0\}}{p^0(\mathbf{X}_i)} \right) Y_i(sr, \mathbf{X}_i) \middle| \mathbf{X}_i \right] \\
&= \mathbb{E}\left[\left(\sum_{j=1}^{D_{\max}} \frac{\mathbf{1}\{D_i = j\}}{1 - p^0(\mathbf{X}_i)} - \frac{\mathbf{1}\{D_i = 0\}}{p^0(\mathbf{X}_i)} \right) Y_i(sr, \mathbf{X}_i) \middle| \mathbf{X}_i \right] \\
&= \mathbb{E}\left[\frac{\left(p^0(\mathbf{X}_i) - \mathbf{1}\{D_i = 0\}\right) Y_i(sr, \mathbf{X}_i)}{p^0(\mathbf{X}_i)\left(1 - p^0(\mathbf{X}_i)\right)} \middle| \mathbf{X}_i \right].
\end{aligned}
$$

Hence I completes the proof of Proposition 1.6.3. □

1.D Test for Instrument Validity

In this appendix, I briefly describe the test for instrument validity developed by Kitagawa (2015) can be applied to my context. In Kitagawa (2015), he considers the simplified case with a binary treatment variable. To fit in my conceptual framework, I extend the analysis to the setting with a multivalued discrete treatment $D_i \in \{0, 1, \cdots, D_{\max}\}$ and a multivalued discrete instrument $Z_i \in \{1, 2, \cdots, Z_{\max}\}$.

In my empirical exercises, I investigate how the marginal effect of the local sex ratio on rural women's migration choice differs by male sibling structure. I first define the derivative of Y_i w.r.t. SR_c evaluated at sr by $\nabla Y_i(sr)$, where SR_c is the level of sex imbalance in county c. My objective is to uncover the treatment effect of having brothers, which is captured by D_i, on rural women's labor migration response to the local sex ratio given by $\nabla Y_i(sr)$. Let P and Q be the conditional probability distributions of $(\nabla Y_i(sr), D_i) \in \mathcal{Y} \times \{j, \cdots, D_{\max}\}$ and $(\nabla Y_i(sr), D_i) \in \mathcal{Y} \times \{0, \cdots, j-1\}$ given Z_i, that is,

$$
\begin{aligned}
P(\mathcal{B}, j | k) &= \Pr(\nabla Y_i(sr) \in \mathcal{B}, D_i \geq j | Z_i = k) \\
Q(\mathcal{B}, j | k) &= \Pr(\nabla Y_i(sr) \in \mathcal{B}, D_i < j | Z_i = k)
\end{aligned}
$$

for Borel set $\mathcal{B} \subset \mathcal{Y}$ and $j \in \{1, \cdots, D_{\max}\}$. According to Imbens and Rubin (1997), Balke and Pearl (1997) and Heckman and Vytlacil (2005), I can obtain

$$
\begin{aligned}
P(\mathcal{B}, j|\,1) \le P(\mathcal{B}, j|\,2) \le \cdots \le P(\mathcal{B}, j|\,Z_{\max}) \\
Q(\mathcal{B}, j|\,1) \ge Q(\mathcal{B}, j|\,2) \ge \cdots \ge Q(\mathcal{B}, j|\,Z_{\max})
\end{aligned}
$$

hold for every Borel set $\mathcal{B} \subset \mathcal{Y}$ and $\forall j \in \{1, \cdots, D_{\max}\}$ if the identifying assumptions hold. These two sets of inequalities are the testable implications under the null hypothesis of instrument validity.

Let $P_n(\mathcal{B}, j|\,k)$ and $Q_n(\mathcal{B}, j|\,k)$ be the empirical distribution of $P(\mathcal{B}, j|\,k)$ and $Q(\mathcal{B}, j|\,k)$ based on the subsample of $Z_i = k$ with size n_k and $\sum_{k=1}^{Z_{\max}} n_k = N$

$$
\begin{aligned}
P_n(\mathcal{B}, j|\,k) &= \frac{1}{n_k}\sum_{i=1}^{n_k} I\{\nabla Y_i(sr) \in \mathcal{B}, D_i \ge j, Z_i = k\} \\
Q_n(\mathcal{B}, j|\,k) &= \frac{1}{n_k}\sum_{i=1}^{n_k} I\{\nabla Y_i(sr) \in \mathcal{B}, D_i < j, Z_i = k\}.
\end{aligned}
$$

Similar to Kitagawa (2015), I test the inequalities for any one pair of adjacent values of Z_i with the following statistic

$$
T_{N,j,k} = \sqrt{\frac{n_{k-1}n_k}{n_{k-1}+n_k}} \max\left\{\sup_{\mathcal{I}\subset\mathcal{Y}} \tilde{P}_{n,j,k}\ ,\ \sup_{\mathcal{I}\subset\mathcal{Y}} \tilde{Q}_{n,j,k}\right\}
$$

with

$$
\tilde{P}_{n,j,k} = \left\{\frac{P_n(\mathcal{I}, j|\,k-1) - P_n(\mathcal{I}, j|\,k)}{\xi \vee \sigma_{P,k}(\mathcal{I}, j)}\right\}\ ,\quad \tilde{Q}_{n,j,k} = \left\{\frac{Q_n(\mathcal{I}, j|\,k) - Q_n(\mathcal{I}, j|\,k-1)}{\xi \vee \sigma_{Q,k}(\mathcal{I}, j)}\right\}
$$

where $\mathcal{I} \equiv [\nabla y(sr), \nabla y(sr)'] \subset \mathcal{Y}$, $-\infty \le \nabla y(sr) \le \nabla y(sr)' \le \infty$; ξ is a user-specified positive constant; $\sigma^2_{P,k}(\mathcal{I}, j)$ and $\sigma^2_{Q,k}(\mathcal{I}, j)$ are consistent estimators of the asymptotic variance of $\sqrt{\frac{n_{k-1}n_k}{n_{k-1}+n_k}}(P_n(\mathcal{I}, j|\,k-1) - P_n(\mathcal{I}, j|\,k))$ and $\sqrt{\frac{n_{k-1}n_k}{n_{k-1}+n_k}}(Q_n(\mathcal{I}, j|\,k-1) - Q_n(\mathcal{I}, j|\,k))$, respectively

$$\sigma^2_{P,k}(\mathcal{I},j) = \left(1-\hat{\lambda}_k\right) P_n(\mathcal{I},j|\,k)\,(1-P_n(\mathcal{I},j|\,k)) + \hat{\lambda}_k P_n(\mathcal{I},j|\,k-1)\,(1-P_n(\mathcal{I},j|\,k-1))$$
$$\sigma^2_{Q,k}(\mathcal{I},j) = \left(1-\hat{\lambda}_k\right) Q_n(\mathcal{I},j|\,k)\,(1-Q_n(\mathcal{I},j|\,k)) + \hat{\lambda}_k Q_n(\mathcal{I},j|\,k-1)\,(1-Q_n(\mathcal{I},j|\,k-1))$$

with $\hat{\lambda}_k = n_k/(n_{k-1}+n_k)$. To jointly test the two sets of inequalities, I use the statistic defined by

$$T_N = \max_{j\in\{1,\cdots,D_{\max}\}} \max_{k\in\{2,\cdots,Z_{\max}\}} T_{N,j,k}.$$

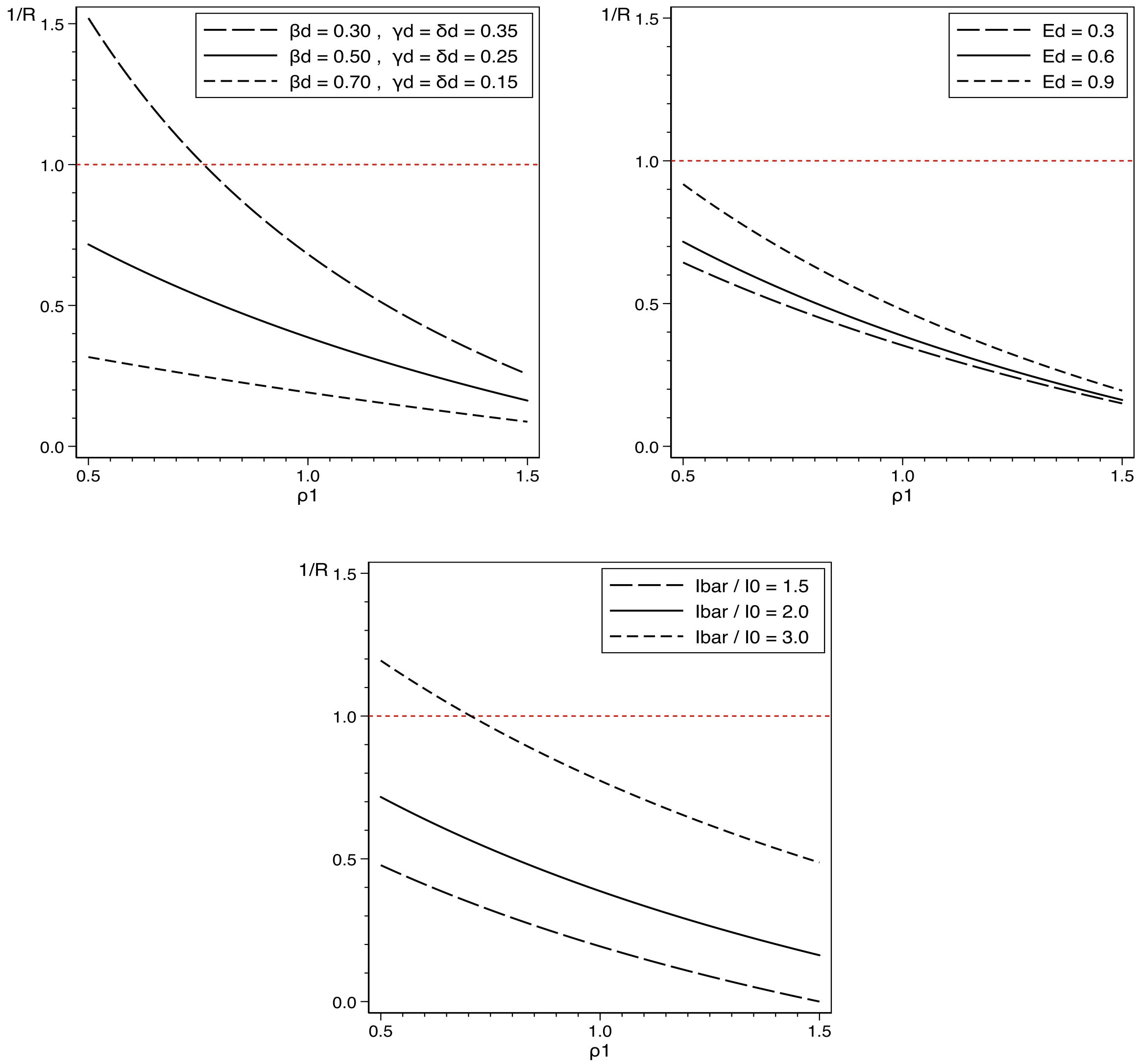
Following the resampling algorithm developed by Kitagawa (2015), I can obtain the empirical distribution of the test statistic T_N by calculating its bootstrap realizations. For a given significance level α, the bootstrap critical value $c_{N,1-\alpha}$ is the $(1-\alpha)$th quantile of the empirical distribution. Once $T_N > c_{N,1-\alpha}$, I will reject the null hypothesis that the instrument is valid. The bootstrap p-value is then given by

$$p = \frac{1}{B}\sum_{b=1}^{B} I\left\{T_N^b > T_N\right\}$$

where T_N^b is a bootstrap realization of T_N and B is the number of bootstrap replications. The test can also be generalized to the case with observable conditioning covariates using a similar procedure, see Kitagawa (2015) for more details.

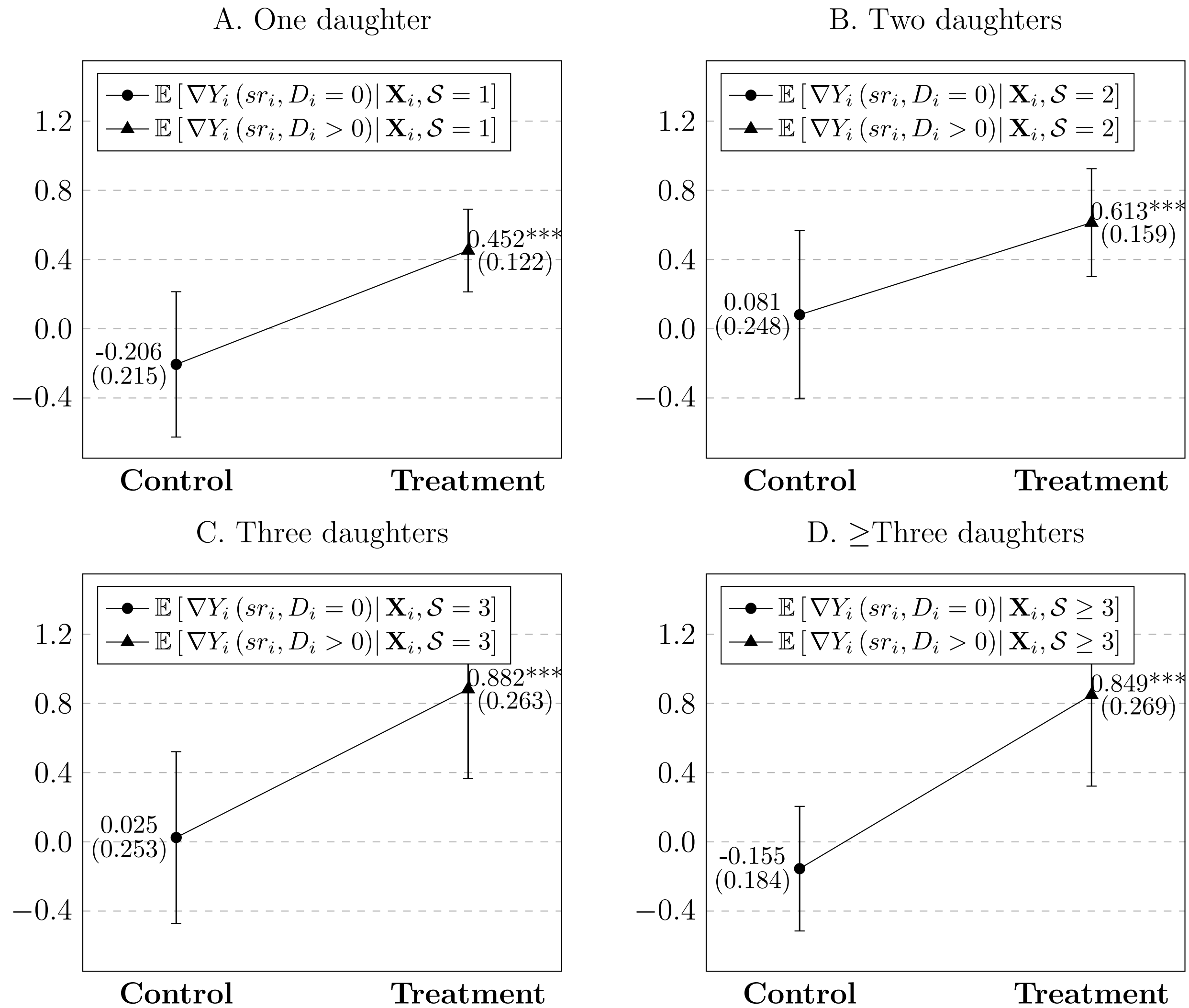
1.E Additional Figures

Figure 1.A1 Relative Impacts of the Two Channels (ρ_1=ρ_2 Changes, Under Alternative Sets of Parameters)



Notes: This figure shows how $1/\mathcal{R}$ varies by ρ_1 (or ρ_2) when ρ_1=ρ_2 under alternative sets of parameters. The default values are $\alpha_d^c = 0.5$, $\alpha_d^\pi = 0.25$, $\alpha_d^\ell = 0.25$, $H_d = 0.6$.

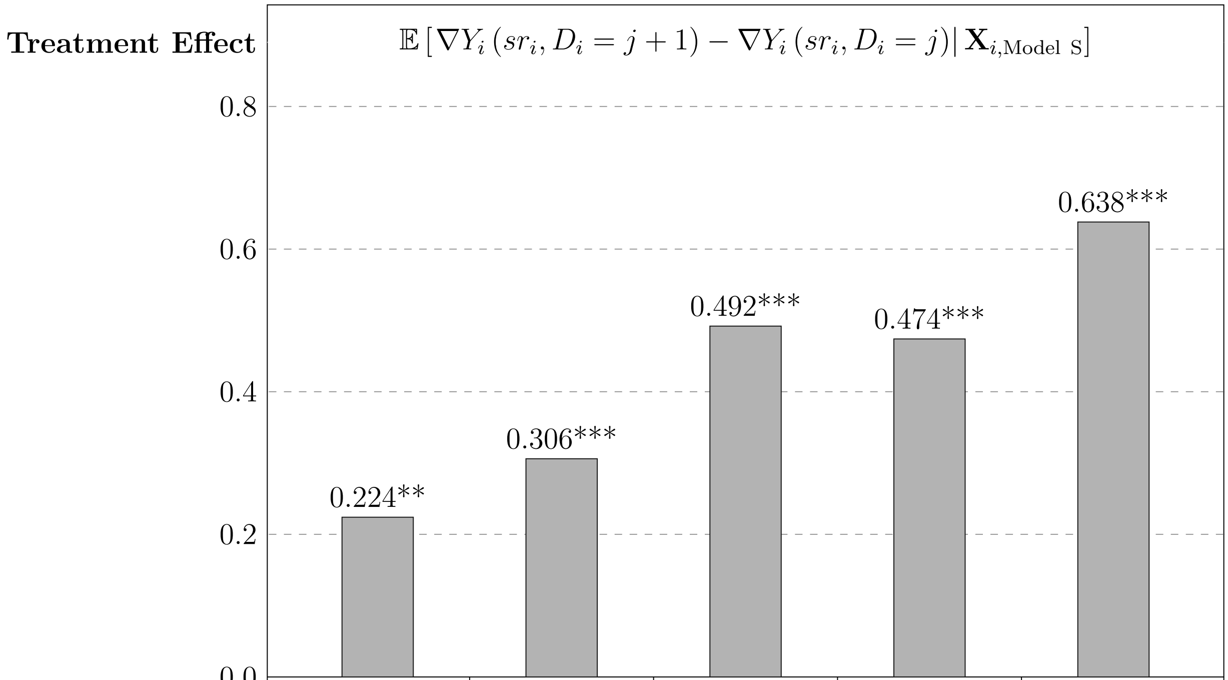
Figure 1.A2 Fixing the Number of Daughters



Notes: Robust standard errors in parentheses. This figure shows the marginal effect of the local sex ratio on the labor migration outcome for rural women with brothers and those without brothers, respectively. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. The parameters are obtained by separately estimating a probit model for the two types of rural women. In Panels A-D, I restrict my sample to families with one daughter, two daughters, three daughters and more than three daughters, respectively. All estimates are conditional on the full set of controls.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 1.A3 Women with j Brothers v.s. Women with $j+1$ Brothers (Full Sample)



	Model 1	Model 2	Model 3	Model 4	Model 5
(s.e.)	(0.099)	(0.107)	(0.120)	(0.120)	(0.131)
p-value	0.024	0.004	0.000	0.000	0.000
Baseline	0.105	0.096	-0.063	-0.076	-0.197

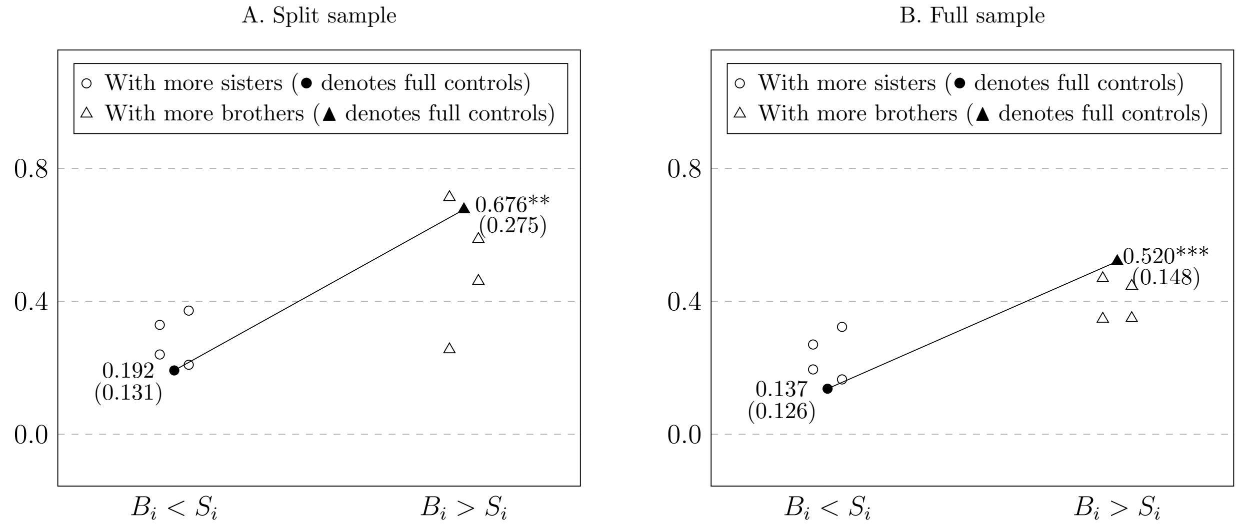
Notes: Robust standard errors in parentheses. D_i represents the number of brothers that the rural woman has. The baseline represents the group without brothers. This figure displays the estimated coefficient on the interaction term of the local sex ratio and the male sibling size of the rural woman in a probit model for rural women's labor migration decision. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 1.A4 Women with More Brothers Than Sisters v.s. Women with More Sisters Than Brothers



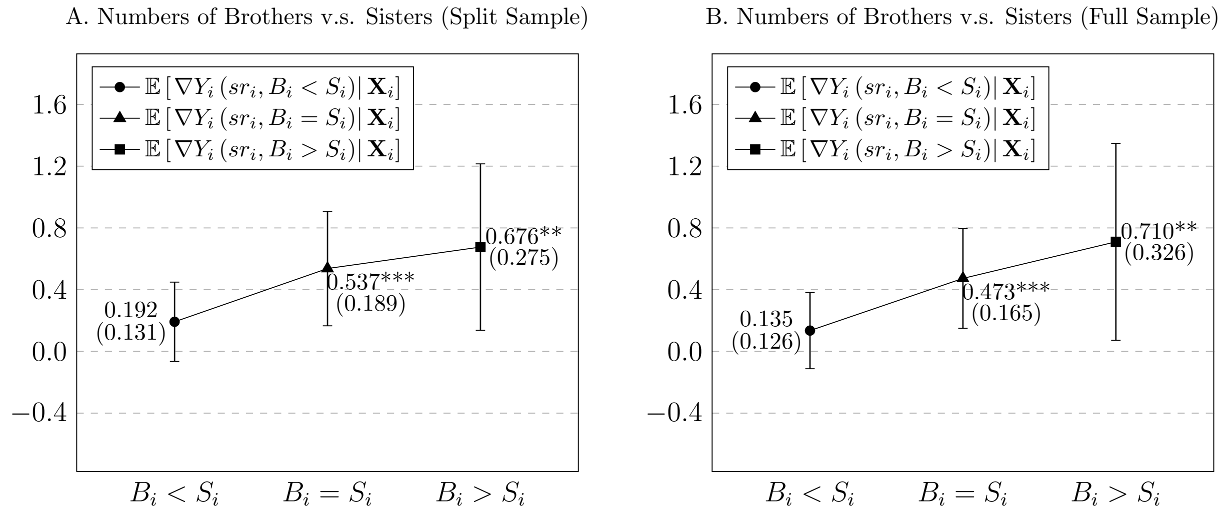
Notes: Robust standard errors in parentheses. B_i represents the number of brothers, and S_i represents the number of sisters. This figure displays the marginal effect of the local sex ratio on the labor migration outcome for rural women with more brothers than sisters and those with more sisters than brothers., respectively. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. The parameters in Panel A are obtained by separately estimating a probit model for the two types of rural women. The parameters in Panel B are obtained by estimating a probit model with an interaction of the local sex ratio and an indicator for whether the rural women has more brothers than sisters. The numbers 1-5 represent Models 1-5.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 1.A5 Treatment Effects on $\nabla Y_i\,(sr_i)$ of Different Sibling Structures



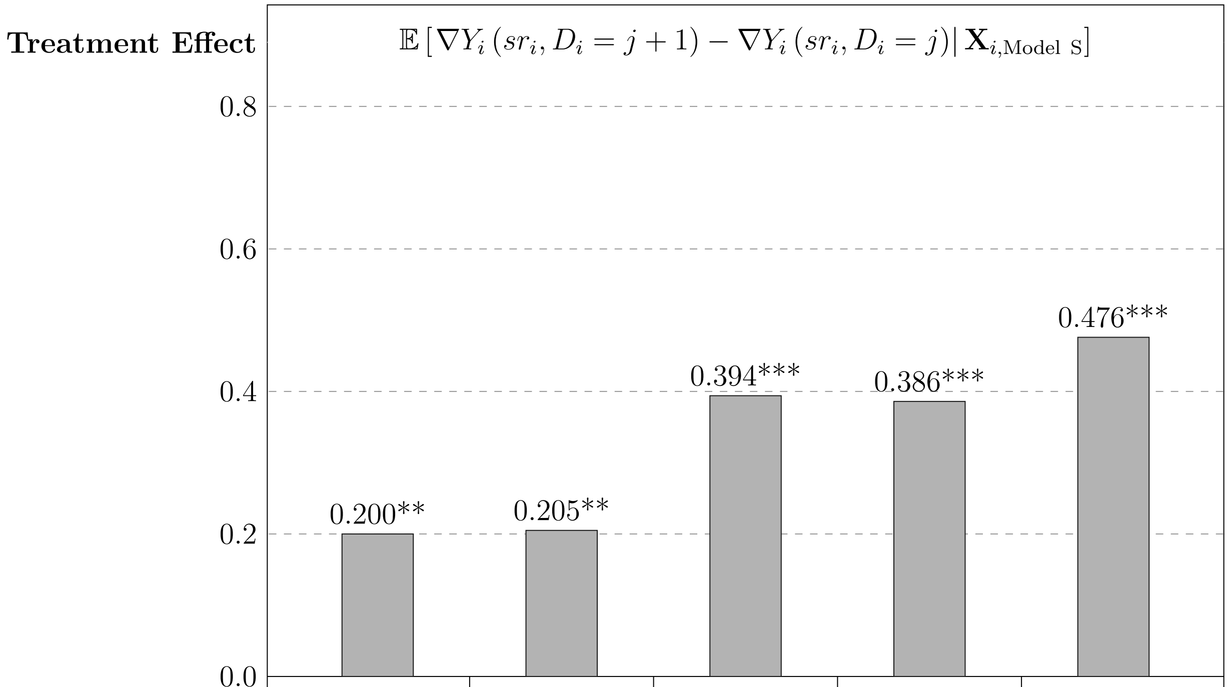
Notes: Robust standard errors in parentheses. B_i represents the number of brothers, and S_i represents the number of sisters. This figure shows the marginal effect of the local sex ratio on the labor migration outcome for rural women with more sisters than brothers, those with equal number of sisters and brothers and those with more brothers than sisters, respectively. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. The parameters in Panel A are obtained by separately estimating a probit model for the three types of rural women. The parameters in Panel B are obtained by estimating a probit model with interactions of the local sex ratio and the sibling structure dummies. All estimates are conditional on the full set of controls.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 1.A6 Women with j Brothers v.s. Women with $j+1$ Brothers (Migration Experience, Full sample)



	Model 1	Model 2	Model 3	Model 4	Model 5
(s.e.)	(0.086)	(0.092)	(0.105)	(0.105)	(0.112)
p-value	0.020	0.026	0.000	0.000	0.000
Baseline	0.139	0.157	0.019	-0.020	-0.050

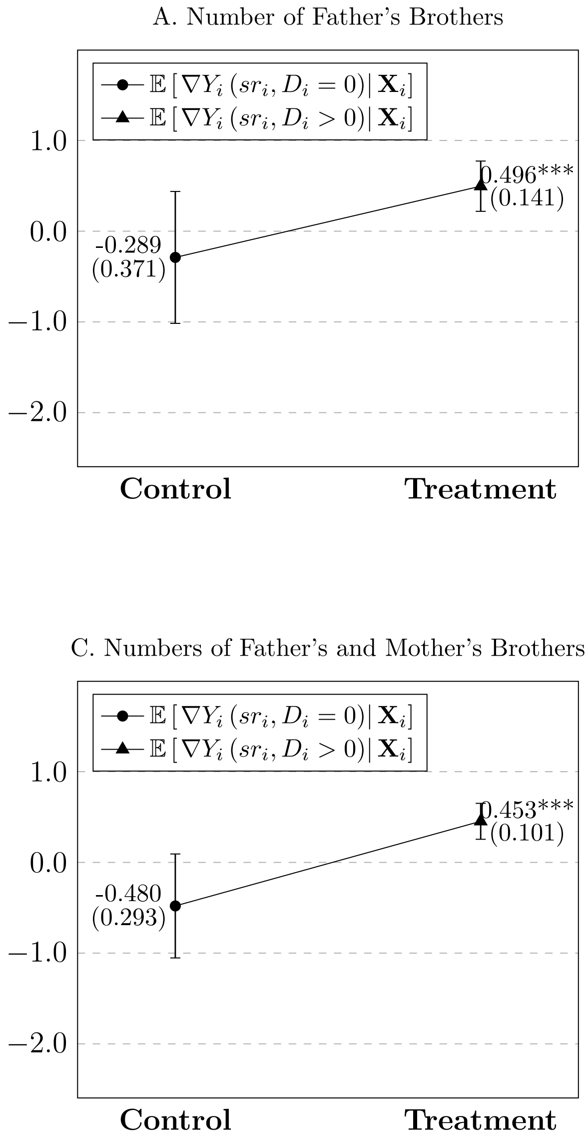
Notes: Robust standard errors in parentheses. D_i represents the number of brothers that the rural woman has. The baseline represents the group without brothers. This figure displays the estimated coefficient on the interaction term of the local sex ratio and the male sibling size of the rural woman in a probit model for rural women's labor migration decision (defined as an indicator for whether the rural woman has ever participated in migratory work). The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 1.A7 IV Estimation: Number of Male Siblings (Full Sample)



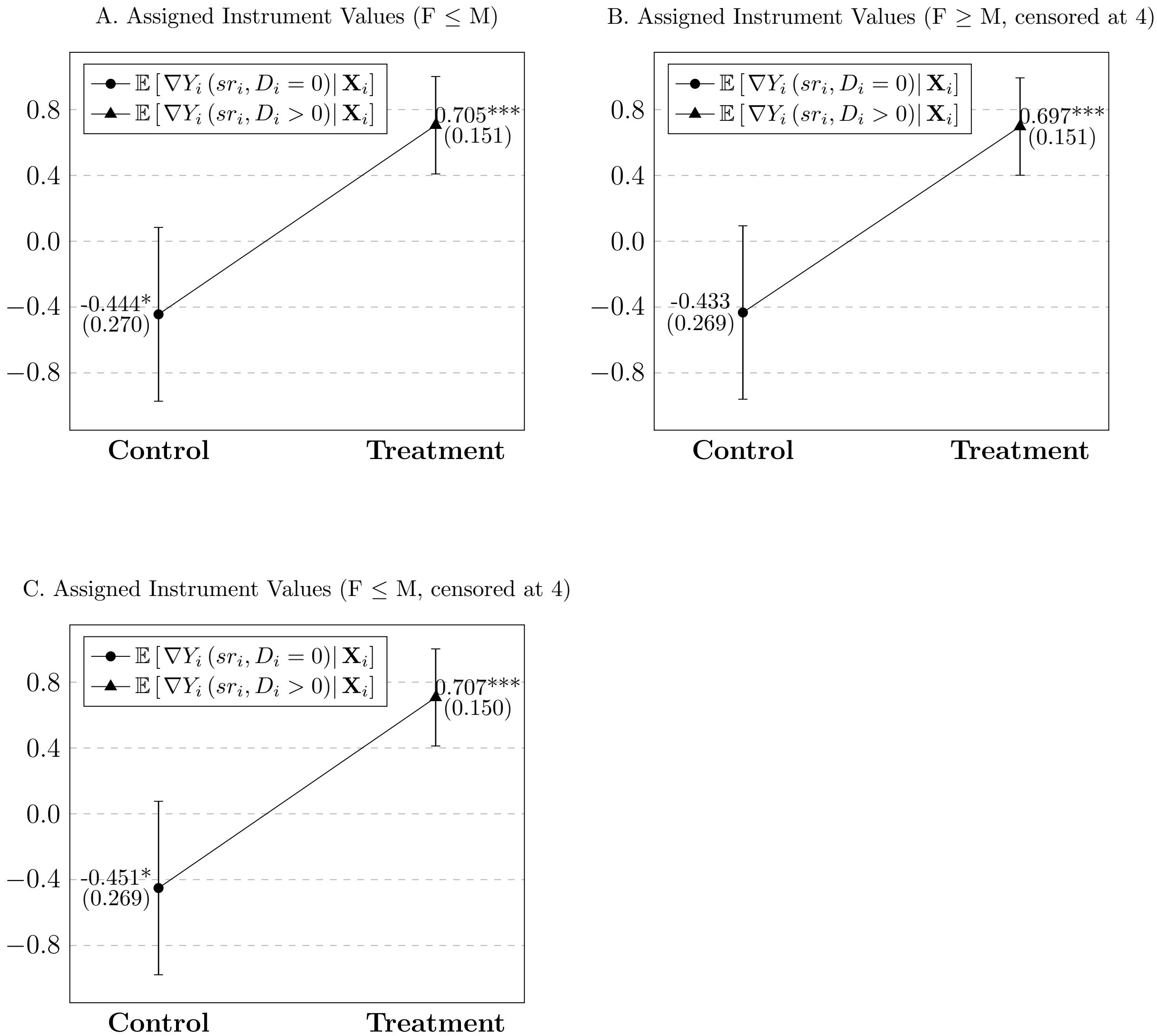
Notes: Robust standard errors in parentheses. This figure displays the marginal effect of the local sex ratio on the labor migration outcome for rural women with brothers and those without brothers, respectively. The parameters are obtained by estimating a probit model with an interaction term of the local sex ratio and the male sibling size of the rural woman. I separately consider four possible instruments for the male sibling indicator: the number of the father's brothers Z_i^m, the number of the mother's brothers Z_i^f, the total number of the parents' brothers $Z_i^t = Z_i^m + Z_i^f$ and the instrument with assigned values Z_i. The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. All estimates are conditional on the full set of controls and the corresponding total number of parental male siblings.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 1.A8 IV Estimation: Male Sibling Indicator (Reconstruction of Z_i)



Notes: Robust standard errors in parentheses. "F" represents the number of father's brothers and "M" represents the number of the mother's brothers. This figure displays additional IV estimation results for the case where the male sibling indicator is considered endogenous. As robustness checks, I create three possible instruments by reconstructing Z_i. On the one hand, I assign larger values to the instrument vector if the mother has ever had more brothers conditional on the total number of parental siblings. On the other hand, the parental male sibling size variables are recoded and censored at 4 if they are larger than 4.The local sex ratio is measured as the county-level sex ratio for the age cohort 16-20. All estimates are conditional on the full set of controls and the corresponding total number of parental male siblings.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

CHAPTER 2

Preference or Endowment? Intergenerational Transmission of Women's Work Behavior and the Underlying Mechanisms†

2.1 Introduction

Economists have long been interested in the issue of married women's labor force participation. A substantial body of literature has attempted to establish the causal relationship between changes in married women's labor supply and changes in standard economic factors including female educational attainment, fertility rates, costs of childcare, divorce risks, and progress in household technology, etc. Recently, growing attention has been devoted to the intergenerational determinants of married women's work behavior. Understanding the link between the employment decisions of married women across generations is also critical to untangling the fundamental forces that shape a society's long-term trend of female labor force participation.

One salient feature in the data of different countries is that there is a strong and positive correlation between women's labor force participation rates of two adjacent generations. Such intergenerational persistence is widely believed to slow down shifts in women's labor supply behavior for any given economic or social change. For example, Boustan and Collins (2014) uncover that the extremely higher labor force participation rates for black women under slavery, coupled with the intergenerational transmission of women's work behavior,

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can account for a significant part of the large and long-lasting racial differences in female labor force participation during the post-Emancipation era. Through intergenerational propagation, any exogenous shock that changes women's labor supply of the current generation may persist over several generations, thus having profound impacts on the evolving pattern of the overall female labor force participation.

At the micro level, how does women's work behavior transmit across generations? Based on several U.S. survey data sets, Fernández et al. (2004) present ample evidence showing a positive association between the labor market status of a man's wife and that of his mother. To be precise, they find that having a working mother significantly increases the probability that a man's wife participates in market work, even after controlling for various background characteristics of both the husband and the wife[1]. Theoretically, the intergenerational transmission of women's employment decisions from mothers-in-law to daughters-in-law can be attributed to two potential mechanisms. First, the influence of maternal work behavior may operate through affecting son's beliefs and views regarding the appropriate gender roles. It is possible that men raised by working mothers are less opposed to the wife's labor force participation and thus more likely to marry women with stronger labor market attachment than the other men. Alternatively, it may also happen that growing up with working mothers has endowed these men with greater household productivity than their peers. This in turn allows their spouses to engage more in market work relative to domestic tasks, making them a better companion for working women.

Although the two potential channels seem to be equally convincing and interesting, Fernández et al. (2004) do not try to empirically test whether either of them is plausible or which one matters more. Motivated by their innovative work, a series of studies that focus on the intergenerational transmission of women's work behavior have emerged (e.g. Morrill and Morrill, 2013; Kawaguchi and Miyazaki, 2009). Some of them attempt to analyze whether the preference channel is the true underlying mechanism using different measures of individual gender role attitudes or subjective satisfaction. For instance, Bütikofer (2013) shows that

[1] Whether the wife's mother worked has no significant effect on the wife's work behavior conditional on the couple's background characteristics.

a married woman's contribution to family income exerts a negative effect on the life satisfaction and financial satisfaction of her husband if her husband was reared by a non-working mother. Both Farré and Vella (2013) and Johnston et al. (2014) document a statistically significant relationship between a mother's and her son's views regarding women's role in the family and the labor market. They also find that a married woman's employment decision is strongly correlated with her husband's gender role attitudes. The authors interpret these findings as supporting evidence for the preference channel.

Yet despite the helpful efforts spent on studying the intergenerational transmission of gender norms, the endowment channel remains largely unexplored. The objective of this paper is to fill the gap in the literature by providing extensive evidence to identify the relative importance of the two competing mechanisms in linking the labor supply choices of a married woman and her mother-in-law. We begin our analysis by replicating the cross-sectional results in Fernández et al. (2004) using the Chinese household survey data. Similarly, we find compelling evidence in favor of the intergenerational correlation of women's work behavior between mothers-in-law and daughters-in-law rather than between mothers and daughters. In particular, we find that having a working mother-in-law is associated with at least a 9 percentage point increase in the probability of working for a married woman.

We next turn to examine the channels through which the effects of mother-in-law's work behavior on a married woman's current employment status occur. First, to test whether the intergenerational relationship works through the channel of preference, we construct indices of men's gender role attitudes as well as subjective well-being. We find that once geographical factors are controlled for, whether a married man holds traditional views towards working women is not significantly affected by the labor force experience of his mother during his teenage years. In addition, even if we take the husband's gender role attitudes into account, there is still a considerable portion of the intergenerational correlation left unexplained. Moreover, we show that a married woman's decision to work will not undermine her husband's subjective well-being regardless of the former labor market status of her mother-in-law. In light of the weak evidence for the preference channel, we posit that the endowment channel is likely to play an important role in facilitating the intergenerational transmission of the labor market choices from mothers-in-law to daughters-in-law.

The major challenge of testing the endowment channel lies in the fact that men's household productivity is usually unobserved in the data. To substantiate the existence of the endowment channel, our strategy proceeds in three steps. First, we compare married men with elder siblings to those without elder siblings. We propose that if the endowment channel is indeed an important underlying mechanism, then we should observe a stronger influence of the mother's work behavior on that of the wife among married men who do not have elder siblings. Second, we compare married couples who coreside with the parents to those who do not live with the parents. We postulate that the intergenerational correlation should be weaker among couples cohabiting with the parents under the endowment channel. Third, we examine the relationship between maternal employment status and household time allocation decisions. Our conjecture is that if men with working mothers tend to be more proficient in household duties, their spouses will be liberated from home production and have a higher labor supply.

The novelty of our tests of the endowment channel is that they circumvent the difficulty of directly measuring men's housework proficiency. In our first test, we take advantage of men's sibling composition and birth order information from the data to proxy for their housework skills. To be specific, in many developing countries such as China, where family culture is deeply influenced by the patriarchal and collectivistic values, gender and birth order are essential determinants in housework allocation among siblings. On the one hand, due to the intense son preference, parents tend to assign a larger share of domestic work to their female children. On the other hand, in societies with family-oriented collectivistic culture, earlier-born children are expected to undertake their family obligation of caring for their younger siblings. Using the Nepal survey data, Edmonds (2006) finds that older girls spend more time than boys on household chores and that the presence of younger boys in the family will increase the workload of older girls. Fafchamps and Wahba (2006) further show that all firstborn children are much more likely to be engaged in domestic tasks. Given the gender effects and the birth order effects, it is highly possible that later-born male children in traditional developing societies have little involvement in household duties even when the mother works outside the home. Building on this idea, we augment our original specification with interaction variables that capture the effects of the husband's birth order on the observed intergenerational link. Conditioning on family size, we find that the marginal effect of mother's work status on the wife's propensity to work is significant only among men who are the firstborn child. As the eldest son in the family is supposed to be more adept at housework than later-born ones, these results demonstrate that the endowment channel should dominate the preference channel in generating the intergenerational correlation in women's work behavior.

Our second test scrutinizes the endowment channel by making use of the parental coresidence status. In China, intergenerational coresidence usually allows the couple to be freed from household tasks because their retired parents would take full charge of the home production. Therefore, for couples cohabiting with the parents, men's housework proficiency might not be a major consideration in the wife's labor market participation decision. As expected, the intergenerational link is only significant among couples who do not live with the parents. To further ensure the validity of the endowment channel, we finally test whether having a working mother affects a married man's time allocation between domestic chores and paid work. We confirm that maternal employment does significantly reduce son's weekly working hours but increase daughter-in-law's without changing the total labor supply of the couple. This suggests that men with working mothers might devote more time to the household sector than their counterparts, making it easier for their spouses to work outside.

The findings above reveal that the endowment channel is likely to be responsible for a large part of the observed intergenerational correlation in female labor force participation. Before concluding our study, we also examine the conditions under which the endowment channel would appear to be weakened. To this end, we look at the heterogeneous effects of mother-in-law's labor market status on the work decisions of skilled women and unskilled women. We hypothesize that the work decision of a skilled woman is less correlated with that of her mother-in-law than their unskilled peers. For one thing, the opportunity costs are often too high for skilled women to exit the labor market upon marriage given their high earning power. For another, the duration of working hours is on average too long, and also unstable for unskilled women to combine career and family without the efficient help from their husbands. Our results show that whether a married woman chooses to work is no longer affected by her mother-in-law's former employment status once her educational level exceeds a certain threshold, while the relationship is highly significant and sizable for low-educated women. This suggests that the husband's household productivity turns out to be more important in the work decisions of unskilled women.

Our paper contributes to the large literature that seeks to explain how labor market outcomes are transmitted across generations, and the pathways through which such intergenerational persistence occurs (see Corak, 2013; Black and Devereux, 2011; Solon, 1999, for excellent review). It is also relevant to a recent strand of research investigating the role of family in passing preferences, attitudes and norms on to the next generation (e.g. Bisin and Verdier, 2001; Doepke and Zilibotti, 2008; Dohmen et al., 2012). In addition, our efforts to empirically test the endowment channel shed more light on the determinants of the intra-household division of labor, complementing the theoretical discussion in Cigno (2007, 2012).

Our work is also related to the burgeoning literature that is interested in marital sorting and how this can feed back into the macroeconomy. One influential contribution is Fernández et al. (2005), which models the relationship between marital sorting, inequality, human capital accumulation and growth. Eika et al. (2014) provides an empirical analysis on how sorting impacts upon household income inequality using data from the U.S. and Norway. Marital sorting also has important implications in our context. For the two channels we study, the positive correlation in women's labor market choices may arise either from assortative matching where women with strong preferences for working match with a man that is most compatible with that desire, or from the increased probability of working for a random woman matching with the considered man. This distinction has macroeconomic consequences. If the intergenerational link is created by matching, then increasing female labor supply today do not necessarily increase female labor supply tomorrow. In contrast, if the relationship does not disappear conditional on the match, then the rise in the proportion of working women of the current generation will lead to a dynamic process affecting female labor force participation over time (Doepke and Tertilt, 2016).

The rest of the paper is organized as follows. Section 2 presents a review of the related background on the two underlying mechanisms. Section 3 describes the data sets we use in the empirical exercises. Section 4 analyzes the intergenerational transmission of women's work behavior. Subsequently, in Section 5, we explore whether the preference channel has important implications for the intergenerational link documented in Section 4. The role of the endowment channel is discussed in Section 6. In Section 7, we study the heterogeneity in the intergenerational correlation between skilled women and unskilled women. The last section concludes.

2.2 Background on the Underlying Mechanisms

Theoretical foundations for both the preference channel and the endowment channel discussed above have been well established in the existing literature. In this section, we provide a brief reformulation of the theories as well as an overview of the related studies.

2.2.1 The Preference Channel

The key feature of the preference channel is the role of maternal employment in the determination of married men's gender role preferences. Particularly, men who were brought up in the modern family in which the mother was a breadwinner differ in their preferences towards having a working wife from their peers growing up in the traditional family in which the mother was purely a housewife. It is claimed that men raised by working mothers tend to be more supportive of their wives' engagement in market activities. This idea can be formally modeled by imposing a utility penalty for having a working wife that challenges the conventional gender roles within a household (Bertrand et al., 2016). Compared to men whose mothers worked, the utility penalty is supposed to be larger for men growing up in the traditional single-earner family. Therefore, ceteris paribus, relative to men whose mother did not work, men with working mothers are more likely to marry a woman who has a greater desire for working.

The insight of the preference channel is consistent with the existing theories of the intergenerational cultural transmission and gender identity formation. Fernández (2013) explicitly models the intergenerational transmission of gender role preferences as an endogenous learning process where individual beliefs are inherited from their parents and updated according to some noisy public signal. In a similar spirit, Fogli and Veldkamp (2011) include the local information transmission as a part of the learning mechanism, arguing that neighbors are also central to the formation of individual beliefs. More generally, Bisin and Verdier (2000, 2001) posit that children acquire their cultural traits and preferences through an adaptation and imitation process which is determined by the direct socialization efforts from parents, and by the indirect influence of the social environment in which they live. A conceptual limitation of their framework is that they regard the couple as a monolith when passing their traits on to the next generation, which cannot be readily applied to the case where the preferences of the wife differ from those of the husband. To address this issue, Cigno et al. (2017) expand the theory in Bisin and Verdier (2000, 2001) by developing a more generalized model that allows for preference heterogeneity. While these studies propose a series of pathways for intergenerational cultural transmission, they mutually emphasize the important role of early socialization from parents in determining children's preferences and the subsequent economic outcomes (Bisin and Topa, 2003; Olivetti et al., 2013). In our context, men developed their gender role attitudes during adolescence mainly by observing the behavior of the adults they are frequently exposed to. Thus, a mother's work decision, to a certain extent, determines whether her son will conform to the conventional gender stereotypes.

2.2.2 The Endowment Channel

The endowment channel provides an alternative explanation for the observed intergenerational pattern in women's work behavior. Unlike the preference channel, men are now assumed to have homogeneous attitudes towards their spouses' work decisions. Specifically, this channel is concerned with the differences in household productivity between men with working mothers and men brought up by non-working mothers. It is suggested that men raised by working mothers are systematically more productive in domestic work than their counterparts, making it easier for their spouses to participate in the labor market. Therefore, the higher probability of working for women whose mother-in-law worked is likely to result from the reduced burden of household duties in response to having a husband better at housekeeping.

The argument of the endowment channel fits into the voluminous literature on the gender division of labor within married couples. Tracing back to the piorneering work of Becker (1965, 1981, 1985), economists have formally articulated that the presence of increasing returns to specialization is a powerful force in creating a sharp division of labor between married partners. Specially, efficient domestic allocation of resources requires that household members should specialize to some extent in either income or child raising activities based on personal comparative advantages, on grounds that there is no perfect substitute for parental care (Cigno, 2007). In this case, the spouse endowed with lower earning potential relative to household productivity should become the main childcarer. Although such a specialization is optimal for the family as a whole, the partner who concentrates on domestic chores is at a relatively disadvantaged position in terms of labor market prospects due to their reduced value of marketable skills. Cigno (2012) rigorously demonstrates that marriage may serve as a commitment device to facilitate cooperation between partners by allowing the main childcarer to credibly threaten divorce, and thus to guarantee division of labor according to comparative advantages. Because of women's biological advantage in caring children, the traditional gender division of labor where women are allocated to household production and men are assigned to market work is still a prevalent phenomenon even in developed countries such as US (Vernon, 2010). Iversen and Rosenbluth (2006) further argue that married women who specialize in household-oriented tasks may dedicate some time to paid employment when the workload of domestic chores permits this, as predicted by the above endowment hypothesis.

The intrinsic logic behind the endowment channel is also related to a recent literature that explores the effect of liberation from housework on female labor force participation (Bittman et al., 2004; Cardia, 2008; de V. Cavalcanti and Tavares, 2008; Dinkelman, 2011;

Greenwood et al., 2005; Coen-Pirani et al., 2010; Shen et al., 2016). For example, Greenwood et al. (2005) construct a dynamic equilibrium model to demonstrate that the technological progress in the household sector has facilitated married women's entrance into the workforce. The flood of new consumer durables, such as washing machine and vacuum cleaner, allows women to spend less time on home production and more time on market activities. A similar point is made by Coen-Pirani et al. (2010), who estimate the impact of household appliance ownership on married women's work decisions using micro-level data from the 1960 and 1970 U.S. Censuses. They also find that the diffusion of household appliances has contributed to the increased labor force participation rate among married women. Apart from the perspective of technological changes, Shen et al. (2016) investigate how married women's allocation of time between household chores and market work is affected by family structure. They show that intergenerational coresidence helps promote female labor supply due to the substantive parental assistance in housekeeping and childcare. In view of the above evidence, for a married woman, the domestic burden should be recognized as one of the key ingredients in deciding whether to combine family and career or not. Thus, if a mother's labor market status indeed changes her son's household skills, then it should also make a difference to her daughter-in-law's propensity to work.

2.3 Data

The data we use in the empirical exercises come from the Chinese General Social Survey (CGSS) conducted in 2008, 2012 and 2013. The CGSS is a national representative continuous survey project run by the Chinese academic institution, which collects cross-sectional data at the household level through face-to-face interviews. The households in the survey are randomly drawn from each sampled community in 29 provinces nationwide[2]. The survey data cover important information about individual characteristics, family background, labor market activities as well as social values.

To construct the samples for our analysis, we focus on married couples where the wife

[2]The two provinces, Hainan and Tibet, are excluded in the sample.

is between the ages of 20 and 50[3]. Since these wife cohorts are of prime working age, we can reduce the influence of life-cycle bias of women's labor supply behavior. In the replication of the cross-sectional results of Fernández et al. (2004), we compare regressions for male respondents to those for female respondents. The male sample consists of all married male respondents whose wives are between 20 and 50 years old, while the female sample contains all married female respondents of age 20 to 50. One may cast doubt on the validity of using the female sample as a comparison. In particular, one might think that the respondents in the female sample are not comparable to the spouses in the male sample we use in terms of observable and unobservable characteristics. It is important to emphasize that the respondents in the CGSS survey are randomly selected within each household, i.e., whether the wife or the husband answers the questionnaire is not determined by the household members[4]. As a result, there should not exhibit any systematic differences between families in which the wife answers the questionnaire and families in which the husband answers.

In our study, the main dependent variable of interest is the work status of the wife, which is defined as a dummy variable equaling to 1 if the wife participated in paid job the week before interview or had a paid job but was on leave temporarily, and zero otherwise. Our key explanatory variable is the former employment status of the respondent's mother. This variable is also a binary variable collected as the response to a recall question, "Did your mother work outside the home when you were 14?" Note that the work variables are defined as non-agricultural employment and women engaged in farm-related occupations are excluded[5].

In both the male and female samples, we can simultaneously obtain the following personal

[3]We exclude those where the wife is at school, retired or disabled.

[4]To ensure survey quality, the CGSS has a team of professional researchers who are responsible for the random sampling design and supervision over the data collection process. The interviewers are also rigorously trained to implement the relevant procedures that determine the eligible respondents in the sample.

[5]In China, agricultural work is usually not separated from home production. More often than not, a Chinese female farmer turns out to be a full-time housewife who bears the responsibility of taking care of the whole family as well. Therefore, including agricultural employment may confound our results.

characteristics of the husband and the wife for each observation: age, years of education, annual earnings, *hukou* status[6] (non-rural *hukou*=1, rural *hukou*=0), political status (Communist Party member=1, otherwise=0), and number of kids. Apart from maternal employment, we also have access to other family background and parental characteristics of the respondent, including father's education, mother's education and family's socio-economic class at the age of 14 of the respondent. The last variable ranges from 1 to 10, where "1" corresponds to the lowest class and "10" the highest class. It is measured by the subjective survey question, "What do you think about your family's socio-economic class when you were 14?" However, no parallel information on these variables is available for the respondent's spouse.

Table 2.1 presents the summary statistics of the above variables separately for the male and female samples. From Table 2.1, we can see that on average both the respondents and their spouses in our samples have received around 12 years of schooling, which is equivalent to a senior high school degree. The mean education level of the last generation is less than 9 years. The labor force participation rate of the wife cohorts is nearly 72%, while only 60.9-62% of the women in the mother cohorts worked in the labor market. It is worth mentioning that both the mean and the standard deviation for each of the variables in Table 2.1 are quite similar between the male and female samples. We also perform the Kolmolgorov-Smirnov test to compare the distributions of these characteristics in the two groups. The corresponding statistics and p-values are displayed in the last two columns. As indicated by the results, we cannot reject the null that the distributions of the variables in the two samples are equal to each other at the 5 percent level.

In Table 2.2, we compare the work status, annual earnings, husband's education and husband's annual earnings among the wives of different education groups. From Panel A, we can see that as education level increases, married women have a higher probability of involving in market work. It can be inferred from Panel B that for those working wives,

[6]The *hukou* status is related to the segmentation of urban and rural labor market in China. This urban-rural dual structure has its root in China's household registration (also known as *hukou*) system, which aims at controlling the migration between urban and rural sectors. Under this system, workers are segregated into two categories—one with rural *hukou* status and the other with non-rural *hukou* status. This classification not only identifies workers by their place of birth but also determines their basic welfare, such as education, employment and social insurance.

their annual earnings are strictly increasing in their educational attainment. Panel C and Panel D show that on the whole, as women become better educated, they are more likely to marry a husband who earns more and who has more years of education. This may be a result of assortative mating in the marriage market where a woman and a man match based on similar characteristics. Thus, when we examine the intergenerational correlation of the work behavior between a man's wife and his mother, it is important to isolate the effect of maternal employment from the effect of marital sorting by controlling for the personal characteristics of both the husband and the wife.

To assess the preference channel, we need to obtain measures of men's gender role attitudes. In the CGSS survey, the respondents were asked whether they agree or disagree with the five opinions summarized in the notes of Table 2.3. The possible responses are 1 for "completely disagree", 2 for "partially disagree", 3 for "neither agree nor disagree", 4 for "partially agree" and 5 for "completely agree". The first four statements describe different aspects of the conventional gender norms regarding women's role in the family and the workplace, while the last one reflects a specific dimension of the non-traditional gender role preferences. To maintain consistency of the evaluation indices, the values assigned to the fifth statement are reverse-coded with 5 referring to "completely disagree" and 1 referring to "completely agree". Thus, for each of the five opinions, the higher value the respondent assigns, the more traditional gender role attitudes he/she holds. We also construct an overall score of gender role attitudes by averaging the answers for the five statements.

Table 2.3 reports the means and the distributions of the six attitude indices described above. We observe that the means of these indices are mostly between 2 and 3. In addition, the married men in our sample are more likely to answer 2 or 4 for each statement while less likely to answer 1 or 5, suggesting that the majority of them hold neither neutral nor extreme views towards gender roles. Moreover, we find that the proportions assigning 4 and 5 to the first opinion amount to nearly 56%, which are far greater than those for the other four opinions. This indicates that the married men in our sample have a higher tendency to respond positively to the "men outside, women inside" intra-household division of labor relative to the other four dimensions of traditional gender stereotypes.

2.4 Intergenerational Relationship of Women's Work behavior

In this section, we formally investigate the relationship between a married woman's propensity to work and her mother-in-law's former labor market status. To this end, we make use of the spousal information and maternal employment history of the male respondents to estimate married women's labor force participation decision. Our regression model is specified as follows:

$$\mathbf{1}\{\textit{Wife work}\} = \beta\mathbf{1}\{\textit{Mother work}\} + X'\delta + \epsilon \tag{2.1}$$

where $\mathbf{1}\{\textit{Wife work}\}$ and $\mathbf{1}\{\textit{Mother work}\}$ are the indicator variables of the wife's current work status and the previous work status of the husband's mother when he was 14; X is defined as a vector of control variables.

Table 2.4 presents the probit estimation results. In Column 1, we employ the parsimonious specification that measures the unconditional effect of the labor supply choice of the husband's mother on the wife's current work status. Consistent with Fernández et al. (2004), the baseline result suggests that the labor force participation decision of the wife is positively and strongly correlated with whether the husband's mother worked. Specifically, the probability that the wife works is 17.1% higher if her husband was brought up by a working mother, and this effect is statistically significant at the 1 percent level. We control for the geographical variables that capture the respondent's current place of residence in Column 2. The regional effects are measured at the provincial level and constructed as a set of dummy variables. This is to rule out the possibility that people tend to choose their spouses who come from the same place as themselves, and women from the same place may have similar labor supply pattern due to some systematic factors. We find that the coefficient estimate on the labor market status of the husband's mother remains significant at the 1 percent level with a magnitude slightly smaller than that of Column 1.

One major concern with the above estimates is that they may reflect the influence of the husband's family background, such as the family wealth of the husband, that could also have an effect on the wife's work behavior. In response to this concern, we then add the husband's family background characteristics in Column 3. The variables are father's education, mother's education and family's socio-economic class at the age of 14 of the husband. Another concern that may plague our analysis is that the intergenerational link between the labor force choices of the wife and the husband's mother may be driven by the positive assortative mating in the marriage market. This could happen because people tend to search for married partners who have comparable personal characteristics that might be strongly affected by maternal employment. In this sense, the labor market status of the husband's mother is likely to capture the effects of the personal characteristics of the couple themselves. To address this issue, Column 4 further adjusts for various individual characteristics of the married couple: husband's and wife's age, education, political status, and *hukou* status, husband's income and number of children. We also include a quadratic term in wife's age. The results in Table 2.4 show that the estimated coefficient on maternal work status is robust to the addition of these variables. The significance level remains unchanged, and the effect size does not attenuate dramatically. The marginal effect in Column 3 is 11.5 percentage points, and it decreases slightly to 9 percentage points in Column 4. The difference between the two estimates can be roughly interpreted as the effect of assortative matching.

One may argue that mothers who are strongly attached to the labor market are more likely to migrate to places with more job opportunities. To better control for this possibility, we restrict our sample to individuals who did not migrate across provinces in Column 5. Doing so doest not alter our coefficient estimate of interest in terms of both economic and statistical significance. Yet, for men who stay in the local province, we may worry that they have much higher chances to marry a woman from the same place who also has low mobility and that the observed strong correlation in women's work behavior is simply a result of some common factors affecting the non-migrants. It is necessary to test whether the difference between the local sample and non-local sample is statistically significant. We include an interaction term between the dummy variables indicating whether the husband's mother worked and whether the repsondent migrated across provinces and find that the corresponding coefficient is not significant.

Apart from mother-in-law's labor market status, most of the standard economic variables, such as the wife's education, political status and number of children, also have the expected sign and significance[7]. For example, according to the specification in Column 4, an additional year of education raises the chance that the wife engages in market work by 1.5 percentage points, while having one more child reduces the likelihood by 5.1 percentage points. The effect of age on women's labor force participation decision appears to be inverse-U shape. Compared to women who are non-Communist party members, those who are party members are 16.4% more likely to participate in the labor market.

Although the marginal effect of mother-in-law's work status is robust across alternative model specifications, we may still suspect that the intergenerational link is largely the outcome of marital sorting by maternal employment. More specifically, it may be that the main driver of the wife's work decision is her own mother's labor market status, whereas women raised by working mothers prefer to marry those men whose mother also worked. Fernández et al. (2004) investigate this possibility by including the work behavior of both the husband's and the wife's mother in the estimation for the wife's labor force participation. Since we do not have simultaneous information of mother's work status for both spouses, we cannot partial out the influence of the labor supply choice of the wife's own mother. However, we still attempt to confront this problem by estimating a parallel set of specifications to Table 2.4 for the female respondents.

The estimation results based on the female sample are reported in Table 2.5. In all specifications, we find that having a working mother increases the probability that a married woman works outside the home, but this impact is statistically insignificant when we control for the parental or personal characteristics of the wife. Moreover, the marginal effect of mother's work status is tremendously smaller in magnitude than that of mother-in-law's as shown in Table 2.4. This result is not surprising as we have included the woman's educational achievement in our estimation which may capture the influence of maternal employ-

[7] Full results are available upon request.

ment. According to Johnston et al. (2014), human capital accumulation is a key potential avenue through which working mothers affect their daughters' labor market behavior. Taken together, our results in Table 2.4 and Table 2.5 may reveal the fact that the effect of having a working mother on a woman's labor force participation is not direct and is likely to operate through the acquisition of education, while mother-in-law's work behavior reflects some different factors that have direct relevance to a married woman's labor supply choice.

Collectively, our results in this section suggest that mother-in-law's former work status plays an essential part in determining a married woman's labor force participation decision and that the driving forces of the intergenerational association are not the background characteristics of the married couple.

2.5 Testing the Underlying Mechanism: The Preference Channel

As mentioned in the introduction, two possible mechanisms may contribute to generating the intergenerational link in women's work decisions. In this section, we attempt to test whether the preference channel has important impact on the formation of the intergenerational correlation. The hypothesis is that the past maternal employment is a critical factor in shaping men's attitudes regarding the role women should fulfill in the family and the labor market. In particular, a working mother is more likely to pass on to her son positive views about married women's labor force participation. This indirectly leads to his match with a working woman in the marriage market, or raises the probability that his wife works conditional on the match.

2.5.1 Maternal Employment, Men's Gender Role Attitudes and Married Women's Work Decisions

We first examine the intergenerational effect of maternal employment on men's gender role attitudes. In general, one's values and beliefs are formed in the social context where he was brought up, and jointly determined by his own experience and family background. To isolate the influence of maternal employment, we control for the married man's personal characteristics, family socio-economic status and parental education. In addition, for a married man, maternal work behavior may reflect the gender norms that prevails within the area where he comes from or where he resides in. Thus, we add the geographical dummies as in the previous section to separate the effect of maternal employment from the confounding regional factors. In order to comprehensively evaluate men's gender values, we use the overall score of the attitude indices, IndexM, as the dependent variable.

The regression results are given in Table 2.6. We begin by using the mother's former work status as the only independent variable in Column 1. The point estimate on the maternal employment indicator is negative and statistically significant at the 1 percent level, suggesting that men who grew up with working mothers are less likely to adhere to the conventional gender stereotypes. To test the sensitivity of our result, Columns 2 to 4 sequentially add regional dummies, parental characteristics and the married man's personal characteristics, and Column 5 uses the specification of Column 4 but restricts the sample to non-migrants. Interestingly, in Column 2, we find that when we control for region of residence, the effect of mother's labor market choice is rendered insignificant and reduced to about one half of its initial value. The estimated coefficient on mother's work status decreases dramatically as we include additional controls and is nearly identical to zero in the last regression. This indicates that the geographical variables almost completely capture the influence of maternal employment on son's gender role preferences. We also perform the same set of regressions using the five individual attitude indices as dependent variables separately, which does not alter our conclusion.

Our results in Table 2.6 can be interpreted as reflecting the influence of cultural diversity across different regions in China. Particularly, mother's work behavior is likely to represent certain pervasive norms within each province, thus the importance of regional fixed effects in explaining the variation of men's gender role attitudes may be attributable to cultural variation across provinces. To confirm our interpretation, we further examine the distributions of the attitude indices[8]. Using kernel density estimation, we find that the shapes of

[8]The corresponding figures of the distributions of the attitude indices are not presented to save space and are available upon request.

the distributions of men's gender role attitudes vary substantially across geographical areas. On the other hand, striking similarities are observed among neighboring provinces in their attitude distributions. In addition, we also compare the overall distributions of the attitude indices between men with working mothers and men with non-working mothers. Though the former type of men seem to hold a more egalitarian view towards gender roles, the distributions of their attitudes almost overlap in each of the index variables and the differences appear to be very small. This evidence assures us that geographical factors are essential in shaping men's gender role preferences, while the influence of maternal work behavior might be typically a manifestation of regional culture.

As discussed above, to some degree maternal employment affects men's gender role attitudes. However, this does not imply that the intergenerational correlation in women's work behavior is the outcome of intergenerational transmission of gender norms. To further explore the relationship between spousal preferences and married women's work decisions, we add the overall attitude index of the husband in the regressions explaining the wife's employment status[9]. The results are provided in Table 2.7. The set of specifications in Table 2.7 mirror those in Table 2.4 with the inclusion of the additional attitude measure. As can be seen from Table 2.7, the wife's propensity to work is significantly and negatively related to the husband's gender role attitude for all specifications, implying that a more traditional man tends to have a non-working wife. More importantly, although we adjust for the husband's gender role attitudes, the estimated coefficient on whether the husband's mother worked remains highly significant with a magnitude only slightly smaller than that in Table 2.4. In other words, even if the preference channel holds, there is still a large portion of the intergenerational link left unexplained.

[9]One might worry that the effect of having a working mother-in-law cannot be separated from the effect of husband's preferences by simply adding the attitude index in the regression because the husband's gender role preferences are also affected by his mother's labor supply choice. However, we find that the difference in gender role attitudes among men with working mothers versus those with non-working mothers is very small and statistically insignificant after controlling for geographical factors. In addition, even if the husband's gender role attitudes and maternal work experience are correlated to a certain extent, excluding one of them from our regression does not significantly change the estimated effect of the other. As argued in Farré and Vella (2013), this suggests that mother-in-law's work behavior may not only reflect the role of intergenerational cultural transmission, but also involves other components that influence the wife's work decision.

2.5.2 Does Having a Working Wife Reduce Men's Subjective Well-Being?

Under the preference channel, a fundamental assumption is that men raised by non-working mothers have a stronger aversion towards having a working wife than their peers whose mothers worked. In Fernández et al. (2004), they model this story by assuming that men with non-working mothers will suffer disutility from having their wives participate in market work. Thus, another approach for testing the preference mechanism is to investigate the relationship between individual utility and spousal employment status for these two types of men. According to Frey and Stutzer (2002), a sensible tradition in economics to measure utility is to rely on people's evaluations of their life satisfaction or happiness. It is shown that reported subjective happiness in large surveys can serve as a valid and empirically adequate indicator of human well-being. Bütikofer (2013) uses general life satisfaction and financial satisfaction reported by the respondents as proxies for utility, and finds that the wife's income contribution significantly reduces a married man's well-being if he grew up in a traditional family. However, these results do not directly reveal that the satisfaction of these men is negatively affected by the wife's labor force participation. Since income contribution is closely related to bargaining power within couples, even if a man is not averse to having a working wife, he may still feel upset when his wife earns relatively more.

In this subsection, we examine how a married man's subjective well-being will be affected by his wife's work status. Similar to the questions about gender role attitudes, the respondents were asked to assess the degree of happiness in their life from 1 "extremely unhappy" to 5 "extremely happy". In addition to the quality of marriage, which is influenced by spousal employment status and number of children, married men's subjective well-being is also determined by various sociodemographic and socioeconomic factors. In the estimation of the determinants of happiness, we control for the series of variables that are used in Table 2.4. The results of ordered probit estimation are presented in Table 2.8. In the top panel of Table 2.8, we aim to estimate how the wife's work behavior affects the subjective happiness of a representative man in our sample. The results show that men with working wives have a higher level of happiness than men whose wives do not work, but this effect is not significant. We then investigate whether the impact of spousal employment on happiness differs between men with working mothers and men with non-working mothers. To this aim, we replace the wife's work indicator with two interaction terms in our regressions. These terms are the main independent variables of interest, which capture the heterogeneous responses to the wife's involvement in market work for the two types of men. From the bottom panel of Table 2.8, we observe that most of the estimated coefficients on the two interaction variables are positive but none of them are statistically significant in all specifications. This indicates that the wife's labor market participation does not significantly improve or undermine the well-being of a married man regardless of the former labor market status of his mother.

2.6 Testing the Underlying Mechanism: The Endowment Channel

In this section, we seek to understand whether the endowment channel can serve as an important pathway for the intergenerational transmission of women's work behavior. In this channel, it is assumed that men who have a working mother tend to be endowed with higher household productivity than their peers, making it possible for their wives to allocate sufficient time to market work. It should be clarified that the endowment channel does not operate through changing married men's attitudes towards sharing the domestic burden. Controlling for regional fixed effects, we find no significant relationship between maternal employment and son's gender role attitudes regarding whether household tasks should be divided equally within couples. Besides, the descriptive statistics of the attitude indices show that the average married men in our sample hold an opinion that is between "partially agree" to "neutral" about sharing housework, and only 14.1% of them have opposite attitudes. Provided that the vast majority of married men are willing to take an equal share of household responsibilities, the husband's housework capability appears to be particularly important in the decision of the wife's labor force participation.

2.6.1 Sibling Composition

The major difficulty in studying the endowment channel is that individual household productivity is usually unavailable in the data. This is also one of the main reasons why the preference channel is emphasized overwhelmingly more in the current literature. To address this issue, our first strategy is to utilize the sibling composition information of the male respondents to infer their ability in doing housework.

To be specific, we first compare the strength of the intergenerational correlation in the mother's and the wife's work status between two groups of married men. One group of them have elder sisters and the other one of them do not. In China, son preference is a widespread phenomenon that is deeply ingrained in its history and tradition. If a family has both a daughter and a son, the daughter is usually supposed to undertake the larger proportion of household chores. This is especially true when the daughter is older than the son. Thus, even if a man is raised by a working mother, it is still very likely that he is not skilled in housework at all when he has an elder sister. It is reasonable to assume that men without elder sisters are systematically more productive in the household sector than those who have elder sisters. Under this assumption, if the endowment channel is indeed an important underlying mechanism, then a stronger positive association should be established between maternal and spousal employment decisions among those men who have no elder sisters.

To test our hypothesis, we replace the indicator variable of mother's work status in our original specification with two interaction terms, $\mathbf{1}\{\textit{Mother work}\} \times \mathbf{1}\{\textit{No elder sister}\}$ and $\mathbf{1}\{\textit{Mother work}\} \times \mathbf{1}\{\textit{Have elder sister}\}$. These two variables are used to capture the intergenerational relationship for men without elder sisters and men with elder sisters, respectively. The sibling composition category with respect to whether the married man has any elder sister is also included. We further adjust for the influence of family size by adding four dummy variables indicating whether the male respondent has one sibling, two siblings, three siblings and more than three siblings, respectively. The first column in Table 2.9 presents the results from probit estimation of the wife's work decision with the interaction terms, sibling composition indicator and family size variables included. We find a positive and statistically significant coefficient estimate on the first interaction term, while the estimated coefficient on the second interaction is substantially smaller and lacks significance. This pattern implies that maternal employment status is significantly and positively correlated with the wife's work decision for men without elder sisters, but the effect is no longer significant and diminishes drastically for men who have elder sisters. The interpretation of these results is twofold. First, the results suggest that the husband's housework proficiency is the key intermediate variable linking a married woman's work behavior and her mother-in-law's. Second, it is indicated that the endowment channel dominates the preference channel in explaining the intergenerational correlation. If this is not the case, i.e., the preference channel is strong enough, then we should also observe a significant marginal effect of mother's work status among men with elder sisters.

In addition to elder sisters, the presence of elder brothers may also lead to a lower probability of men's acquisition of household skills during childhood or adolescence. Compared to younger children, in Chinese families, older children are expected much more to help out with domestic duties. It is therefore sensible to conjecture that a married man is more likely to have a lower level of housework ability if he has an elder brother. We now classify our sample of men according to whether they have elder brothers or not and estimate the wife's labor force participation equation which includes the two new variables, $\mathbf{1}\{Mother\ work\} \times \mathbf{1}\{No\ elder\ brother\}$ and $\mathbf{1}\{Mother\ work\} \times \mathbf{1}\{Have\ elder\ brother\}$. The results are displayed in Column 2 of Table 2.9. Clearly, the intergenerational correlation is significant only when the married man has no elder brother. Now that both the presence of elder sisters and elder brothers matter, in Column 3 we then divide the male respondents in our sample into three disjoint sets based on whether they have elder siblings or not. The three groups are those who have no elder siblings, those who have elder sisters, and those who have elder brothers but no elder sisters, respectively. Consistent with the findings in the first two columns, it is shown that maternal employment status has a significant effect on the wife's probability of working only if the man does not have elder siblings[10].

[10]Regression analysis based on more detailed birth order information gives us similar results.

One may be concerned that birth order and sibling composition could also have an impact on the formation of men's gender role preferences, thereby affecting the intergenerational persistence of work choices between a married man's mother and his wife. For example, if mothers have a higher tendency to transmit their values and attitudes to the firstborn child relative to the later-born ones, then the significant intergenerational link observed among married men who are the eldest son might be mainly operating through the preference channel. To find out, we reestimate the regressions in Columns 1 to 3 with IndexM as the dependent variable, and the results are reported in Columns 4 to 6 of Table 2.9. It turns out that none of the sibling dummies are statistically significant, suggesting that men's attitudes with respect to gender identity are not correlated to their sibling compositions or birth orders.

To sum up, significant evidence of the intergenerational link in women's work behavior can only be found among couples in which the husband should have developed proficient household skills if he was reared by a working mother. These results together imply that the endowment channel is the more crucial mechanism that generates this observed link.

2.6.2 Parental Coresidence Status

Apart from sibling information, we also look at the living arrangement of the married couple. As filial piety is considered as one of the most essential virtues for Chinese people, it is not a rare phenomenon in China that married children coreside with their parents or parents-in-law. Intergenerational coresidence usually allows the wife to have more time for market activities since her parents or parents-in-law would offer a tremendous amount of assistance in both childcare and household duties. Thus, for couples residing with the parents or parents-in-law, the husband's housework capability seems to be relatively unimportant in the wife's labor market participation decision. If the positive intergenerational correlation of women's work behavior is operating through the endowment channel, then we should see a weaker link among the married couples cohabiting with the parents.

It has long been argued that family structure should be treated as endogenous since cohabitation with parents or parents-in-law is an option that can be selected by the couple (Sasaki, 2002). In particular, those women who themselves have stronger preferences for working may choose to live with their parents or parents-in-law. However, in our sample, we find that 21.8% of the couples coreside with at least one of their parents if the wives are employed and 24.2% if the wives are not. Moreover, after controlling for a series of characteristics, such as education, age and family background, the wife's labor market status does not significantly affect the probability that the couple cohabits with the parents and that the marginal effect is about minus 0.8 percentage point. These facts and evidence suggest that there does not appear to be any effect of self-selection occurring through the wife's labor supply choice on parental coresidence status. On the other hand, intergenerational coresidence may also hinder married women from involving in market work because of the need to look after aging parents. To deal with such concern, we control for parents' age in our regression. We also perform the same exercises for younger cohorts whose parents are supposed to be younger and reach similar conclusions.

As in the previous subsection, we add interactions between the former employment status of the husband's mother and dummy variables as to parental coresidence status in order to compare couples who live with the parents to those who do not. We also include one indicator for parental coresidence status in our model. Table 2.10 reports our major findings. In the first column, a contrast is made between the couples coresiding with both parents and those who do not live with any one of the parents. Consistent with our expectation, the estimated effect of maternal employment on the probability that the wife works is significantly positive if the couple does not cohabit with the parents, whereas it is statistically insignificant for those who live with the parents. We further make use of the information of coresidence with the mother as well as coresidence with the father. Columns 2 to 4 display the correpsonding results, which exhibit similar patterns. In addition, we find that whether the couple cohabits with the parents is not significantly correlated with the wife's employment status across all specifications. This provides some evidence for the exogeneity of parental coresidence.

Though we have shown that our analysis is not seriously threatened by endogenous selection of living arrangement, for robustness we employ the instrumental variables approach to reestimate the first specification in Table 2.10. The potential endogeneity comes from the indicator variables with respect to the couple's family structure. If the choice of living arrangement is correlated with some unobserved factors affecting the wife's propensity to work, then we would expect the cohabitation indicator as well as the two interactions between maternal employment and parental coresidence status in our specification to be endogenous. To achieve identification, the key is to find appropriate instrumental variables (IVs). Since maternal employment is predetermined, we only need to exploit exogenous variation in parental coresidence status. The two cross terms can then be instrumented by interacting the mother's work status with the exogenous variations in the choice of living arrangement, as suggested by Wooldridge (2010).

We consider two candidate instruments for the cohabitation dummy variables: the average percentages of cultivated land devoted to rice and wheat respectively in the husband's home province when he was aged 5-15, which is the time when individuals are most likely to form their behavioral prescription[11]. These instruments measure the prevalence of rice farming and wheat farming in the social environment surrounding the husband during his childhood and adolescence. According to the innovative rice theory of Talhelm et al. (2014), people living in the rice-growing regions tend to be more interdependent and collectivistic than those in the wheat-growing areas. The idea is that rice cultivation involves building elaborate irrigation systems that requires intensive cooperation among neighboring farmers, which facilitates the formation of collectivistic cultures and holistic thinking styles. In addition, the massive labor requirements of rice growing also encourages family members to live and work together in order to avoid starvation, making large families with multiple generations more predominant. In contrast, wheat farmers do not coordinate with each other as growing wheat entails much lighter workload and no irrigation is needed. This in turns fosters cultures with more individualism and independence where people typically ad-

[11]The data are drawn from the Chinese statistical yearbooks. We also construct alternative instruments based on two types of changes. First, we measure prevalence of rice or wheat farming as ratios of the food cultivated land area rather than the total cultivated land area, where the latter includes regions for food crops, cash crops and other crops. Second, we change the age period 5-15 to 3-13 and 7-17, respectively. Using these alternative instruments yield similar results.

here to a nuclear family model. Vandello and Cohen (1999) also show that family structure is closely associated with collectivism and suggest using the fraction of multi-generational households as a proxy for the degree of collectivism of a region. Since farming practices affect cultural preferences for collectivism and individualism, we believe that married children are more likely to coreside with their parents if they come from regions with a higher share of cultivated rice area.

We expect that our instruments do not have a direct impact on the wife's decision to work based on the following reasons. First and foremost, there is no evidence that rice and wheat lead to distinct gender norms that are relevant for women's work behavior. By regressing the attitude index on our instruments, we confirm that the husband's gender role preferences are not significantly influenced by his early exposure to the rice or wheat culture in his hometown. Second, the dominant type of farming in a region depends on exogenous environmental suitability, like soil and weather conditions, which should not be related to whether the wife participates in the labor force or not. Third, the rice share or wheat share are characteristics of regional agricultural systems, while our study focuses on women's non-agricultural employment. Last but not least, our instruments are measured as percentages of total cultivated land, and these ratios do not reflect the share of agriculture of the corresponding province and thus should not affect non-agricultural job opportunities.

We now report the IV estimates in Columns 5 to 7 of Table 2.10. Using the share of rice-cultivating area as instrument in Column 5, we find that the intergenerational link between the mother's and the wife's work behavior is only significant for couples not living with the parents, which is consistent with our previous findings. In Column 6, we employ wheat area share as alternative instrument and Column 7 includes both instruments in the estimation. The results remain unchanged. The instruments pass the underidentification test and the Hansen J-test for overidentifying restrictions. In addition, the F-statistics for the joint significance of the instruments in the first stage regressions are very large, which suggests that the instruments have substantial explanatory power for the endogenous variables.

As a final robustness check, we apply the Lewbel (2012)'s method for estimation of our model. This technique allows the identification of structural parameters in regression models with endogenous regressors in the absence of traditional identifying information such as external instruments. Identification is then achieved by assuming heteroskedasticity and having regressors that are uncorrelated with the product of heteroskedastic errors, which is a feature of many models with endogeneity[12]. The linear probability specification in our context automatically satisfies these restrictions. The results are presented in the last column, which are similar to the regular IV estimates in previous columns.

In this subsection, we have shown that the intergenerational link in women's work decisions is only significant among couples who do not cohabit with the parents. When there is little demand for the husband's labor in home production, for instance, when the couple resides with the parents who are likely to provide housework services, the intergenerational correlation is no longer significant.

2.6.3 Intra-Household Time Allocation: Implications from the Couple's Working Time

To provide more solid evidence for the endowment channel, we explore how the intra-household time allocation decision is affected by the former labor market status of the husband's mother. Ceteris paribus, if having a working mother really improves a married man's household skills, then he will spend more time on housework than his peers as he has more comparative advantages in home production. Accordingly, a married woman will increase her labor supply if her mother-in-law worked as a result of having a husband who can offer more help in the household.

One may suspect that the effect of maternal employment on married son's housework time could also work through the preference channel since non-traditional men tend to be more willing to share the domestic chores with their spouses. However, as explained at the beginning of this section, only a small fraction of the married men in our sample are reluctant to offer assistance to their wives in household production. More importantly, we find that mother's work experience does not significantly influence son's attitudes regarding

[12]This approach is essentially moment-based estimation, see Lewbel (2012) for more technical details.

the division of housework between married couples.

As we do not have data for time spent on housework, we instead exploit the couple's labor supply information to shed light on the issue of household time allocation. In CGSS, the labor supply of both the respondent and his/her spouse are provided and measured by hours worked per week. We begin by establishing the relationship between maternal employment status and married son's labor supply. The upper panel of Table 2.11 presents our regression results for the husband's weekly working hours. The set of control variables are parallel to those in Table 2.4. We also include the overall attitude index in each of our specifications to investigate whether the husband's gender role preferences are central to his labor supply behavior. As shown by the results, there is no significant association between a married man's gender role attitudes and his labor supply choice even if we do not control for any background characteristics. This provides suggestive evidence that the husband's time allocation decision does not depend on his attitudes towards gender roles.

In addition, we find that having a working mother significantly reduces a married man's labor supply by at least 1.65 hours per week. This partly supports our hypothesis that men with working mothers are likely to spend more time on home production. To gain a better understanding, we also estimate the relationship between the work status of the husband's mother and the wife's labor supply. Reported in the lower panel of Table 2.11, we observe that a married woman will have significantly higher labor supply if her husband was brought up by a working mother. Conditional on the full set of characteristics, women who have a working mother-in-law will allocate nearly 2.31-2.42 hours more on market work per week than their peers. Since the weekly hours worked are censoring at zero for those who choose not to work, we also replicate the estimations in Table 2.11 using the Tobit regression model. The results are very close to those obtained from OLS estimation.

Overall, we take the evidence presented in this section as supportive of the idea that the endowment channel is the dominant mechanism that underlies the intergenerational transmission of women's work behavior from mothers-in-law to daughters-in-law.

2.7 Further Discussion: Heterogeneous Effects across Skilled and Unskilled Women

Our main results, which are presented in Section 4, capture the average effect of maternal employment on the wife's work behavior. In this section, we explore whether the impact varies across women with different individual characteristics. As analyzed above, mother-in-law's work status affects a married woman's decision to work primarily through changing her husband's household productivity. However, it is also plausible that when the woman receives a sufficiently high income from working, she will participate in the labor market regardless of her husband's capability in housework. Similar things may happen if the woman's required working time is relatively short. In this case, the intergenerational link between the labor supply choices of a married woman and her mother-in-law may differ according to the woman's earning power or workload.

To empirically examine this issue, we look at the heterogenous effects between skilled and unskilled women. As skilled women generally have high potential earnings, it would be costly and irrational for them to exit the labor force after marriage. In addition, skilled women usually work fewer hours and have a more stable work schedule, making it possible for them juggle their jobs and housework even without the help of their husbands. Our summary statistics in Table 2.12 show that the duration of women's working time decreases as education increases. For instance, a typical working day is nearly nine-to-five on average (five business days with two days off) for those working women with above college education. On the other hand, the weekly hours worked for unskilled women have a larger variance even if we standardize this statistics with the respective mean value. This indicates that the working hours for the less educated group are quite unstable. In light of the huge discrepancy between skilled and unskilled women in terms of potential income and time constraint, we conjecture that the labor market participation decision of a skilled wife will not be largely constrained by her partner's household productivity. Hence, we propose the hypothesis that compared to unskilled women, the intergenerational correlation between the work decisions of a skilled wife and her mother-in-law will be significantly weaker.

To test this, we consider married women whose education level is primary school, middle school, high school and above college, respectively. Our strategy is to examine whether and how the impact of mother-in-law's labor force status on a married woman's work choice varies by education categories. To be specific, we augment the regressions in Table 2.4 by interacting mother-in-law's work status with four indicator variables for the married woman's educational attainment. The results are reported in Table 2.13. The coefficient estimates on the interactions with primary school and middle school are positive and statistically significant for all specifications, while the statistical significance of the other two interactions no longer retains once we control for the personal or background characteristics of the married couple. For women with only a primary school diploma, the effect of mother-in-law's work behavior is substantial: having a working mother-in-law raises their probability of working by at least 12.7%.

While we tend to interpret the heterogenous effects as mainly driven by differential earning power or workload, there are two other potential explanations that reconcile these results. From Section 6, the intergenerational correlation diverges depending on the husband's birth order or the couple's parental cohabitation status. One possibility is that unskilled women tend to marry less educated men and that the lower education of the husband is a result of being the first-born son who needs to help with the household chores. Alternatively, it may be that better educated couples are more likely to coreside with the parents. However, based on our regression sample we do not find any significant effect of the husband's birth order on his schooling outcomes or any self-selection of high educated couples into coresidence. This suggests that our heterogenous effects are uncorrelated with these confounders.

On the whole, we document evidence that the effect of mother-in-law's employment status on a married woman's labor supply choice is weaker for women with higher educational attainment, which may reflect higher opportunity costs of dropping out of the workforce or less tight time constraint for combing career and family. As a consequence, these women are less sensitive to their husband's household productivity when making the labor market participation decision. Our findings imply that policies aimed at boosting female labor force participation rate could be more effective if they are targeted at women with lower education.

2.8 Conclusion

In a seminal paper, Fernández et al. (2004) find that the labor force participation decision of a married woman is positively correlated to that of her mother-in-law. One potential mechanism that can account for this remarkable intergenerational correlation in women's work behavior is the transmission of attitudes and beliefs within families. In this sense, men's preferences for having a working wife are influenced and shaped unconsciously by the labor supply choices of their mothers. Another possibility is that having a working mother forces men to help with domestic tasks during their childhood or adolescence, making them more productive in the household sector and thus a better partner for working women. While various studies have investigated the role of the preference channel, the endowment channel has remained largely unexplored due to the lack of data for household skills. Our paper contributes to this recent literature by examining the relative importance of the two potential channels in relating the work decisions between mothers-in-law and daughters-in-law.

Using the Chinese household survey data, we confirm that a married woman has a significantly higher probability of working when her husband was brought up by a working mother, even after conditioning on a wide range of background characteristics. We subsequently analyze whether the effect of mother-in-law's labor supply behavior on a married woman's intention to work occurs through the preference channel. Our results are threefold. First, we find that maternal employment does not have a significant impact on son's gender role attitudes once we control for geographical effects. Second, the coefficient on mother-in-law's work status remains robustly intact when we incorporate the husband's gender role preferences in the specification, suggesting that a large fraction of the intergenerational correlation cannot be explained by the preference channel. Third, we demonstrate that having a working wife will not significantly lower a married man's subjective happiness regardless of his mother's former employment status.

Given the weak evidence of the preference channel, a natural question to ask is whether the endowment channel is the true underlying mechanism that drives the intergenerational link between the labor force participation choices of a married woman and her mother-in-law. To address this question, we exploit the information on the husband's sibling composition, the couple's parental coresidence status and the intra-household time allocation decisions to circumvent the difficulty of measuring the husband's housework ability. Specifically, we hypothesize that under the endowment channel we should observe a weaker intergenerational correlation among couples where the husband has elder siblings or those who cohabit with the parents. This conjecture arises from the phenomena that elder children of families in developing countries bear most of the household duties and that coresiding parents usually provide a considerable amount of home production services. Therefore, the husband's household productivity would be a less important factor contributing to the intergenerational link for these couples. Consistent with our expectation, we find no significant relationship between a married woman's and her mother-in-law's work status among these groups of couples, implying the dominance of the endowment channel over the preference channel. In addition, we also show that having a working mother is associated with 1.65-2.04 less hours worked per week for men, and in response to having a partner who spends more time on housework women increase their labor supply by 2.31-2.42 weekly working hours. The further discussion on the heterogenous effects of mother-in-law's labor market status on the work decisions of skilled women and unskilled women also reinforces our argument in support of the endowment channel.

To summarize, our paper studies the intergenerational determinants of married women's work decisions and offers some new insights to the underlying mechanisms. We provide extensive evidence in favor of the endowment channel as the dominant mechanism based on the Chinese micro-level survey data. As a following-up project, it would be interesting to conduct a multinational analysis and compare the differences aross various countries. On the other hand, China has experienced striking transformations in the labor market over the past few decades, leading to drastic changes in female labor supply pattern. We think that understanding the relationship between intergenerational transmission in women's work behavior and the long-term dynamics of female labor force participation in China would be a promising area for future research.

Tables

Table 2.1 Summary Statistics of the Main Variables

Variable	Male sample			Female sample			K-S test	
	Obs	Mean	Std.dev.	Obs	Mean	Std.dev.	D-stat.	P-value
Husband education	2107	12.26	3.139	2046	12.50	3.262	0.017	0.997
Husband age	2108	39.55	8.305	2047	39.33	8.170	0.015	1.000
Husband party membership	2101	0.194	0.395	2043	0.205	0.404	0.008	1.000
Husband *hukou* status	2105	0.850	0.357	2041	0.827	0.378	0.025	0.879
Husband's annual log-earnings	1919	10.33	0.895	1319	10.51	0.825	0.045	0.238
Wife education	2105	11.68	3.377	2052	12.21	3.296	0.059	0.051
Wife age	2108	37.08	7.758	2052	37.03	7.532	0.021	0.977
Wife party membership	2107	0.072	0.258	2048	0.105	0.307	0.030	0.739
Wife *hukou* status	2101	0.797	0.402	2051	0.830	0.376	0.019	0.992
Wife's annual log-earnings	1140	10.13	0.906	1565	10.05	0.889	0.041	0.315
Wife's work status	2108	0.713	0.453	2052	0.720	0.449	0.008	1.000
Number of kids	2106	1.082	0.600	2051	1.095	0.591	0.005	1.000
Mother education	2093	6.158	4.668	2036	6.604	4.333	0.041	0.331
Father education	2073	7.707	4.592	2021	8.237	4.233	0.043	0.281
Family class at 14	2099	3.863	1.844	2046	4.117	1.958	0.054	0.093
Mother's work status	2108	0.609	0.488	2052	0.620	0.486	0.013	1.000

Notes: "Std.dev." is the abbreviation of "Standard deviation", "D-stat." is the abbreviation of "D-statistic", and "K-S test" is the Kolmogorov-Smirnov test. The Kolmogorov-Smirnov test performs the Kolmogorov-Smirnov equality-of-distributions test between two groups, where D-statistic denotes the largest difference between the two distribution functions. The null hypotheses of equality of distributions cannot be rejected for all female characteristics at the 5 percent level.

Table 2.2 Summary Statistics for Wives of Different Education Groups

Wife education groups	Male sample			Female sample		
	Obs	Mean	Std.dev.	Obs	Mean	Std.dev.
	A. Work status of wife					
Primary school	202	0.520	0.501	131	0.435	0.498
Middle school	564	0.574	0.495	484	0.562	0.497
High school	680	0.716	0.451	653	0.698	0.459
Above college	659	0.886	0.318	784	0.884	0.321
	B. Log annual income of wife					
Primary school	91	9.543	0.858	82	9.207	0.922
Middle school	247	9.633	0.894	309	9.550	0.844
High school	346	10.05	0.810	499	9.902	0.814
Above college	455	10.57	0.760	675	10.49	0.711
	C. Husband's education					
Primary school	202	8.743	2.855	131	7.718	2.785
Middle school	564	10.26	2.410	483	10.04	2.469
High school	679	12.36	2.314	649	12.22	2.306
Above college	659	14.95	2.013	783	15.05	2.061
	D. Log annual income of husband					
Primary school	179	9.849	0.819	84	9.865	0.743
Middle school	502	9.985	0.847	278	10.14	0.780
High school	629	10.32	0.838	388	10.37	0.744
Above college	608	10.77	0.811	569	10.87	0.741

Table 2.3 Distribution of Men's Gender Attitudes

Attitudes[a]	Mean[b]	Distribution				
		1	2	3	4	5
Index1	3.340	6.080%	21.96%	16.33%	42.77%	12.87%
Index2	2.920	8.650%	34.17%	20.26%	29.94%	6.990%
Index3	3.070	7.880%	26.79%	22.88%	35.32%	7.120%
Index4	2.170	27.17%	42.32%	17.92%	11.37%	1.220%
Index5	2.340	18.27%	45.77%	21.86%	11.54%	2.560%
IndexM	2.770					

Notes: a. The respondents were asked whether they agree or disagree with the following five opinions:
Index1: Men should concentrate on career, while women should specialise in home production.
Index2: Men are by nature more outstanding than women.
Index3: It is better for women to have a good marriage than a good career.
Index4: Female employees should be laid off first during times of recession.
Index5: Household tasks should be shared equally between the husband and the wife.

b. The possible responses for the first four statements are 1 for "completely disagree", 2 for "partially disagree", 3 for "neither agree nor disagree", 4 for "partially agree" and 5 for "completely agree". In contrast, the values assigned to the fifth statement are reverse-coded with 5 referring to "completely disagree" and 1 referring to "completely agree", so as to maintain consistency of the evaluation indices. The attitude "IndexM" means the average of five attitude indices. For each of the five opinions, the higher value the respondent assigns, the more traditional gender role attitudes he/she holds.

Table 2.4 Probit Estimation of Wife's Work Decision: Marginal Effects (Mother-in-law)

	Dependent variable: Wife work				
	(1)	(2)	(3)	(4)	(5) Local sample
Mother work	0.171***	0.140***	0.115***	0.090***	0.090***
	(0.018)	(0.019)	(0.021)	(0.021)	(0.025)
Couple controls	No	No	No	Yes	Yes
Parent controls	No	No	Yes	Yes	Yes
Regional effects	No	Yes	Yes	Yes	Yes
Observations	2,108	2,108	2,055	1,860	1,403

Notes: Standard errors in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 2.5 Probit Estimation of Wife's Work Decision: Marginal Effects (Mother)

	Dependent variable: Wife work				
	(1)	(2)	(3)	(4)	(5) Local sample
Mother work	0.095***	0.079***	0.038	0.026	0.048
	(0.020)	(0.020)	(0.023)	(0.028)	(0.034)
Couple controls	No	No	No	Yes	Yes
Parent controls	No	No	Yes	Yes	Yes
Regional effects	No	Yes	Yes	Yes	Yes
Observations	2,052	2,052	2,006	1,274	817

Notes: Standard errors in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 2.6 Man's Gender Attitudes and Mother Work Status

	Dependent variable: Husband's gender attitudes (IndexM)				
	(1)	(2)	(3)	(4)	(5) Local sample
Mother work	-0.098***	-0.048	-0.030	0.012	-0.001
	(0.032)	(0.033)	(0.036)	(0.036)	(0.042)
Husband controls	No	No	No	Yes	Yes
Parent controls	No	No	Yes	Yes	Yes
Regional effects	No	Yes	Yes	Yes	Yes
Observations	1,678	1,678	1,630	1,622	1,213

Notes: Standard errors in parentheses. The table only reports the regressions with the overall attitude index "IndexM" as dependent variable to save space. We also run a parallel set of regressions on the individual indices separately, but this does not change our conclusion.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 2.7 Man's Gender Attitudes and Wife Work Decision

	Dependent variable: Wife work				
	(1)	(2)	(3)	(4)	(5) Local sample
Mother work	0.169***	0.131***	0.105***	0.076***	0.070**
	(0.021)	(0.022)	(0.024)	(0.025)	(0.030)
Attitudes	-0.076***	-0.082***	-0.074***	-0.046***	-0.044**
	(0.017)	(0.017)	(0.018)	(0.018)	(0.021)
Couple controls	No	No	No	Yes	Yes
Parent controls	No	No	Yes	Yes	Yes
Regional effects	No	Yes	Yes	Yes	Yes
Observations	1,554	1,554	1,509	1,358	997

Notes: Standard errors in parentheses. The table only reports the regressions with the overall attitude index "IndexM" as a proxy for the husband's gender role preferences to save space. We also run a parallel set of regressions that include the individual indices separately, but this does not change our conclusion. The coefficients on "Mother work" in different settings are close to the results displayed in Table 2.4.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 2.8 Man's Happiness and Wife Work Status

	Dependent variable: Husband's happiness				
	(1)	(2)	(3)	(4)	(5) Local sample
a. Pooled sample:					
Wife work	0.095	0.077	0.060	0.030	0.021
	(0.064)	(0.066)	(0.066)	(0.076)	(0.088)
Mother work	0.087	0.040	-0.015	-0.029	-0.098
	(0.059)	(0.062)	(0.066)	(0.073)	(0.085)
Couple controls	No	No	No	Yes	Yes
Parent controls	No	No	Yes	Yes	Yes
Regional effects	No	Yes	Yes	Yes	Yes
Observations	1,558	1,558	1,555	1,385	1,019
b. Sample with interaction:					
Wife work ×	0.060	0.075	0.061	0.046	0.043
Mother work	(0.089)	(0.092)	(0.092)	(0.104)	(0.120)
Wife work ×	0.132	0.079	0.060	0.013	-0.003
Mother not work	(0.091)	(0.093)	(0.094)	(0.105)	(0.123)
Mother work	0.137	0.043	-0.016	-0.053	-0.132
	(0.107)	(0.111)	(0.113)	(0.127)	(0.147)
Couple controls	No	No	No	Yes	Yes
Parent controls	No	No	Yes	Yes	Yes
Regional effects	No	Yes	Yes	Yes	Yes
Observations	1,558	1,558	1,555	1,385	1,019

Notes: Standard errors in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 2.9 Estimation Results for the Endowments Channel I: Sibling Status

	Dependent variable					
	Wife work			Husband's gender attitudes		
	(1)	(2)	(3)	(4)	(5)	(6)
Mother work × (No elder sister)	0.092*** (0.023)	-	-	0.016 (0.039)	-	-
Mother work × (No elder brother)	-	0.088*** (0.023)	-	-	0.016 (0.039)	-
Mother work × (No elder siblings)	-	-	0.094*** (0.023)	-	-	0.016 (0.039)
Mother work × (Have elder sister)	0.064 (0.056)	-	0.069 (0.056)	0.516 (0.576)	-	0.268 (0.599)
Mother work × (Have elder brother)	-	0.029 (0.060)	-	-	-0.190 (0.429)	-
Mother work × (Have elder brother but not sister)	-	-	0.058 (0.066)	-	-	-0.160 (0.441)
(Have elder sister)	0.019 (0.052)	-	0.012 (0.055)	-0.240 (0.389)	-	-0.154 (0.392)
(Have elder brother)	-	0.073 (0.047)	0.071 (0.048)	-	0.545 (0.332)	0.506 (0.346)
Couple controls	Yes	Yes	Yes	Yes	Yes	Yes
Parent controls	Yes	Yes	Yes	Yes	Yes	Yes
Regional effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,860	1,860	1,860	1,464	1,464	1,464

Notes: Standard errors in parentheses. We also run a set of regressions that are parallel to those in Columns 4-6 but use the individual attitude indices as the dependent variable separately. The results remain unchanged and are not reported to save space.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 2.10 Estimation Results for the Endowments Channel II: Parental Coresidence Status

	Dependent variable: Wife work							
	Probit regression				Instrumental variables regression			
	(1) Parent	(2) Mother	(3) Father	(4) Both	(5) IV_1[a]	(6) IV_2[a]	(7) IV_1,IV_2[a]	(8) HeteroIV[b]
Mother work × (Parent not cohabit)	0.092*** (0.030)	0.089*** (0.029)	0.081*** (0.027)	0.089*** (0.029)	0.099** (0.047)	0.102** (0.047)	0.097** (0.047)	0.117*** (0.033)
Mother work × (Parent cohabit)	0.079 (0.051)	-	-	-	0.043 (0.125)	0.033 (0.124)	0.034 (0.125)	0.106 (0.065)
Mother work × (Mother cohabit)	-	0.064 (0.052)	-	0.010 (0.082)	-	-	-	-
Mother work × (Father cohabit)	-	-	0.089 (0.060)	0.081 (0.094)	-	-	-	-
Couple controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohabitation dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,077	1,077	1,077	1,077	1,077	1,077	1,077	1,077

Notes: Standard errors in parentheses.

a. The first instrumental variable "IV_1" used in columns (5) & (7) is the average percentage of total cultivated land in each province devoted to rice during the years when husband was aged 5-15. The second instrumental variable "IV_2" used in columns (6) & (7) is the average percentage of total cultivated land in each province devoted to wheat during the years when husband was aged 5-15.

b. In the colunmn (8), we adopt the method of instrumental variables estimation using heteroskedasticity-based instruments proposed by Lewbel (2012), which are denoted as "HeteroIV". We also apply this method respectively to the other three model specifications, which does not dramatically alter our results. In these regressions, the coefficient estimate on the "*Parent not cohabit*" interaction ranges from 0.093 to 0.112 and are significant at the 1 percent level, while the other interaction is statistically insignificant. Besides, the instruments pass the under-identification test, weak-identification test and the Hansen J-test for over-identifying restrictions. The testing statistics are not displayed in the table to save space.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 2.11 Estimation Results for the Endowments Channel III: Intra-household Time Allocation

	Dependent variable: Working hours				
	(1)	(2)	(3)	(4)	(5) Local sample
a. Effect on husband's working hour:					
Mother work	-5.256***	-4.706***	-2.943***	-1.647*	-2.039**
	(1.389)	(0.698)	(0.826)	(0.848)	(0.998)
Attitudes	0.541	0.660	0.575	0.001	0.179
	(0.875)	(0.940)	(1.020)	(1.142)	(1.268)
Couple controls	No	No	No	Yes	Yes
Parent controls	No	No	Yes	Yes	Yes
Regional effects	No	Yes	Yes	Yes	Yes
Observations	1,379	1,379	1,345	1,045	774
b. Effect on wife's working hour:					
Mother work	5.322***	3.876***	3.439***	2.422***	2.306**
	(1.266)	(1.193)	(0.842)	(0.888)	(1.058)
Attitudes	-3.491***	-3.127***	-2.883**	-1.043	-0.842
	(1.335)	(1.096)	(1.218)	(0.936)	(0.847)
Couple controls	No	No	No	Yes	Yes
Parent controls	No	No	Yes	Yes	Yes
Regional effects	No	Yes	Yes	Yes	Yes
Observations	1,441	1,441	1,403	1,091	796

Notes: Standard errors in parentheses. The table only reports the regressions with the overall attitude index "IndexM" as a proxy for the husband's gender role preferences to save space. We also run a parallel set of regressions that include the individual indices separately, but this does not change our conclusion. In addition, we also examine the relationship between maternal employment status and the total weekly hours worked of the family, and find that whether the husband's mother worked has no significant effect on the couple's total labor supply.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 2.12 Summary Statistics for the Wife's Working Hours in Different Education Groups

Wife education groups	Statistics			
	Observations	Mean	Standard deviation	Std.dev./Mean
Primary school	115	56.13	17.00	0.303
Middle school	343	52.97	15.10	0.285
High school	506	46.67	12.25	0.263
Above college	567	43.13	9.651	0.224

Notes: "Std.dev." is the abbreviation of "Standard deviation".

Table 2.13 Heterogeneous Effects of Mother-in-Law's Work behavior on Skilled and Unskilled Women

	Dependent variable: Wife work				
	(1)	(2)	(3)	(4)	(5) Local sample
Mother work × (Primary school)	0.199***	0.181***	0.177***	0.127**	0.129**
	(0.057)	(0.055)	(0.057)	(0.059)	(0.065)
Mother work × (Middle school)	0.130***	0.103***	0.108***	0.130***	0.128***
	(0.033)	(0.033)	(0.033)	(0.034)	(0.040)
Mother work × (High school)	0.067**	0.049	0.056*	0.050	0.048
	(0.032)	(0.032)	(0.032)	(0.033)	(0.038)
Mother work × (Above college)	0.108	0.098	0.107	0.099	0.118
	(0.072)	(0.073)	(0.073)	(0.077)	(0.107)
Couple controls	No	No	No	Yes	Yes
Parent controls	No	No	Yes	Yes	Yes
Education group dummies	Yes	Yes	Yes	Yes	Yes
Regional effects	No	Yes	Yes	Yes	Yes
Observations	2,108	2,108	2,055	1,860	1,403

Notes: Standard errors in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

CHAPTER 3

Nonlinear GMM Estimation in Dynamic Panels with an Application to Value-added Models of Learning

3.1 Introduction

In many economic activities, today's outcome can be very informative about tomorrow's. An important technique to account for such persistence is to establish a dynamic panel data model which includes a lagged dependent variable and an individual specific component. For example, labor economists often study the effect of job training program on productivities conditioning on lagged wage dynamics and worker heterogeneity. A frequently employed estimation procedure for dynamic panel data models is to rely on generalized method of moments (GMM) that exploits a certain set of linear moment conditions after first differencing (Anderson and Hsiao, 1982; Holtz-Eakin et al., 1988; Arellano and Bond, 1991; Ahn and Schmidt, 1995). Despite the appealing asymptotic properties and identification advantages, numerous studies have demonstrated that GMM estimators that make use of only linear moment conditions have very poor finite sample performance.

The most popular linear GMM estimators for dynamic panels are, unarguably, the difference GMM estimator proposed by Arellano and Bond (1991) and the system GMM estimator by Blundell and Bond (1998). The superiority of these two estimators is that they effectively address the endogeneity issue due to the correlation between the lagged dependent variable and the unobserved individual heterogeneity while circumvent the incidental parameter problem (Roodman, 2009). However, the difference GMM estimator is found to suffer from substantial small sample bias, especially when the autoregressive parameter is close to unit root (Blundell and Bond, 1998; Alonso-Borrego and Arellano, 1999). Blundell and Bond (1998) make an important observation that the poor performance of the difference GMM estimator is caused by the weak instrument problem (Staiger and Stock, 1997), and suggest using the system GMM estimator that takes advantage of equations in both levels and differences. Though the improvement in efficiency is significant, some numerical simulations reveal that the system GMM estimator does not always perform well in small samples (Kitazawa, 2001). As the ratio of the variances of the individual effects and the idiosyncratic errors grows, the behavior of the system GMM estimator will deteriorate in terms of asymptotic variance and finite sample bias (Bun and Windmeijer, 2010; Hayakawa and Qi, 2020).

In this paper, I present a general framework for estimating and performing inference on dynamic panel data models by considering the use of nonlinear moment conditions. Unlike the linear moment conditions in both difference and system GMM estimation, the moment conditions proposed in this paper are nonlinear functions of the unknown parameters. The most attractive feature of my approach is that it only requires to know the moment functions of the error terms without the need to find additional variables. Specifically, I construct the nonlinear moment conditions by employing the information from all the available high-order moments of the error components. I show that the use of informative nonlinear moment conditions considerably mitigates the classical weak identification problem in cases where the dependent variable is highly persistent or the variance ratio is large. I also derive explicit analytical expressions for the bias term of both linear and nonlinear GMM estimators via stochastic power-series expansion. A reduction in asymptotic bias of the autoregressive parameter is achieved by using the nonlinear moments. The proposed procedure is readily applicable to other more general model setups where the error terms follow an autoregressive or moving-average process, as well as those allowing for time-varying heterogeneity.

I compare the performance among the difference GMM estimator, the system GMM estimators and the nonlinear GMM estimator through a series of Monte Carlo simulation experiments. In these experiments, I find that the nonlinear moment conditions have dramatically enhanced the estimation accuracy and stability of the GMM estimators for dynamic panels. In particular, the nonlinear GMM estimator outperforms both the difference and system GMM estimators on the criteria of bias and root mean squared error (RMSE) for different values of N and T as well as different parameterizations.

My paper contributes to the study of GMM estimation in dynamic panel data models, and extends it to a more generalized nonlinear setting. Much work in this literature has focused on linear moments in specifications with spherical errors. In this standard case, it is well documented that the system GMM estimator is superior to the difference GMM estimator in terms of finite sample bias and RMSE. As suggested by Blundell and Bond (1998), the instruments in the level equations of system GMM estimation have strong predictive power for the endogenous variables even when the series are very persistent. However, Bun and Windmeijer (2010) point out that system GMM estimation cannot address the weak identification problem when the variance of individual specific effect is large relative to that of idiosyncratic disturbance. Besides, to guarantee consistency of the system GMM estimator, the mean stationarity assumption needs to be imposed on the initial observation. As such, extensive efforts have been made to develop test procedures for the assumption of mean stationarity, see, e.g., Magazzini and Calzolari (2020). The nonlinear moments discussed in this paper outperform the linear moments in the sense that they contain the identifying information within the linear moments while do not require the mean stationarity assumption. Moreover, I show that the nonlinear moments are informative in cases of persistent data and large variance ratio.

Although the idea of nonlinear moments originates from Ahn and Schmidt (1995) and shares similar spirit as the robust moments in Bun and Kleibergen (2013), my work is novel in several aspects. Firstly, my approach can be used to produce high-order moments in addition to first or second moments, which exhausts all nonlinear information in the model. Secondly, the theoretical framework in this paper accommodates more complicated error structures than white noise, including autoregressive errors and moving average errors. Thirdly, my paper is the first to derive the bias of the nonlinear GMM estimator relative to that of the linear GMM estimators, and illustrate how nonlinear GMM estimation is robust to the weak instrument problem of linear GMM estimation under different scenarios.

My work is also related to a large and still growing literature that examines the small sample bias in the presence of weak instruments. There is a long history on the study of weak instrument problem, dating back to Rothenberg (1984), Bound et al. (1995), Staiger and Stock (1997), and Stock and Yogo (2005). More recent contributions include Bun and Windmeijer (2011), Hansen and Kozbur (2014), Kim and Pohlmeier (2016), and Lee and Okui (2012), among others. Most of these studies attempt to demonstrate that weak instruments lead to severe finite sample bias based on higher-order approximation of the estimator (e.g. Hahn and Hausman, 2002; Kim and Pohlmeier, 2016). Another distinct direction in this literature, which does not require the analytical formula for the bias function, examines the bias via Monte Carlo simulations (e.g. Cruz and Moreira, 2005; Hansen and Kozbur, 2014). My paper complements the literature by applying the method of stochastic power-series expansion in Rothenberg (1984) to compare the bias of nonlinear and linear GMM estimators in dynamic panels.

The rest of the paper is organized as follows. In Section 2, I formally present the theoretical framework for constructing nonlinear moment conditions. Section 3 illustrates how the use of nonlinear moments overcomes the weak identification problem in dynamic panels and consequently reduces the finite sample bias of the GMM estimator. Section 4 describes the advocated procedures for estimation and inference, and explores the possible extensions for more complicated error structures. In Section 5 appropriate simulation designs are provided to examine the small sample performance of the linear and nonlinear GMM estimators over different parameterizations. Section 6 applies the method to the estimation of the value-added model with learning dynamics. Section 7 concludes.

3.2 Nonlinear Moment Conditions in Dynamic Panel Models

In this section, I provide an intuitive discussion of the nonlinear moment conditions I construct for estimating dynamic panel data models. My framework differs from the conventional linear GMM estimation in several aspects. First, my method accommodates more complicated error structures, including autoregressive errors and moving average errors. Second, unlike the linear GMM estimators that applies exclusively to linear dynamic panels, I allow the inter-temporal relationship to be embedded in a more general nonlinear model setup. Third, the proposed approach offers a simple and feasible procedure for implementing the tests for autocorrelation in the disturbances.

In the following I formally describe how the nonlinear moment conditions can be derived under the assumption of white noise errors. Consider the standard first-order dynamic panel data model with fixed effects

$$y_{it} = \alpha y_{i,t-1} + \eta_i + \nu_{it} \ , \quad i = 1, \cdots, N; \ t = 1, \cdots, T \tag{3.1}$$

where y_{it} is the outcome variable of the ith unit observed at time period t, η_i captures the unobserved individual heterogeneity and ν_{it} is the idiosyncratic error. I focus on micro panels where N is relatively large and T is small. The autoregressive parameter is assumed to satisfy $|\alpha| < 1$, and the error term $u_{it} \equiv \eta_i + \nu_{it}$ is the standard decomposition of the one-way error component. I continue to impose the following assumption on the disturbances.

Assumption 3.2.1. *$\eta_i \sim i.i.d.\mathcal{N}(0, \sigma_\eta^2)$ and $\varepsilon_{it} \sim i.i.d.\mathcal{N}(0, \sigma_\varepsilon^2)$, η_i and ε_{it} are mutually independent across i.*

For illustrative purposes, I strengthen the set of assumptions in Ahn and Schmidt (1995) by assuming Gaussian distribution on the error components. Under the Gaussian distribution assumption, it is easy to construct high-order moment conditions for identification. Also note that homoskedasticity of idiosyncratic errors over time is potentially too restrictive for panel data. Nevertheless, compared to the heteroskedastic case where $Var\left(\varepsilon_{it}\right) = \sigma_{\varepsilon,t}^2$ (depending on t), the assumption of homoscedasticity serves to reduce the number of unknown parameters without changing the main idea of the analysis.

The standard instrument set in linear GMM estimation for model (3.1) results from the orthogonality conditions $\mathbb{E}\left(y_{is}\Delta\nu_{it}\right) = 0$, $s = 1, \cdots, t-2$ (moments for equations in differences) or $\mathbb{E}\left[\Delta y_{i,t-1}\left(\eta_i + \nu_{it}\right)\right] = 0$ (moments for equations in levels). I call it "linear" because both $\Delta\nu_{it}$ and $\left(\eta_i + \nu_{it}\right)$ are linear functions of the unknown parameter α, i.e.,

$$\begin{cases} \Delta\nu_{it} = \Delta y_{it} - \alpha\Delta y_{i,t-1} \\ \eta_i + \nu_{it} = y_{it} - \alpha y_{i,t-1} \end{cases} .$$

In addition to these linear moments, normality of the error terms gives rise to two different types of high-order moment conditions. The first type of high-order moment conditions are given by the products of ω_{it} from different periods, i.e.,

$$\begin{aligned} & \mathbb{E}\left[\prod_{h=1}^{H} u_{it_h} - (H-1)!! \cdot \sigma_\eta^H \cdot \mathcal{I}(H=2n)\right] \\ = \; & \mathbb{E}\left[\prod_{h=1}^{H} (y_{it_h} - \alpha y_{i,t_h-1}) - (H-1)!! \cdot \sigma_\eta^H \cdot \mathcal{I}(H=2n)\right] = 0 \end{aligned}$$

where $H \in \{2, \cdots, T-2\}$, $\mathbf{1}\{\cdot\}$ is the indicator function, n is an arbitrary integer number, and $n!!$ is the double factorial operator. The sample of H subscripts $\{t_h\}$ is an un-ordered collection of the distinct elements from population $\{3, \cdots, T\}$ without replacement. Hence, the number of moment conditions constructed in this way is

$$\begin{pmatrix} T-2 \\ 2 \end{pmatrix} + \begin{pmatrix} T-2 \\ 3 \end{pmatrix} + \cdots + \begin{pmatrix} T-2 \\ T-2 \end{pmatrix} = 2^{T-2} - T + 1.$$

The second type of high-order moment conditions focus on the power of ω_{it}, i.e.,

$$\begin{aligned} & \mathbb{E}\left[u_{it}^H - (H-1)!! \cdot \left(\sigma_\eta^2 + \sigma_\nu^2\right)^{H/2} \cdot \mathcal{I}(H=2n)\right] \\ = \; & \mathbb{E}\left[(y_{it} - \alpha y_{i,t-1})^H - (H-1)!! \cdot \left(\sigma_\eta^2 + \sigma_\nu^2\right)^{H/2} \cdot \mathcal{I}(H=2n)\right] = 0 \end{aligned}$$

where H is limited to any positive integer, i.e., $H \in \mathbb{N}^+$. Therefore, by construction, this generates an infinite number of moment conditions.

The above two sets of moment conditions are nonlinear functions of the autoregressive parameters α and ρ. Under the Gaussian distribution assumption, one can easily obtain higher order information of the unknown parameters, and construct infinitely many nonlinear moment conditions.[1] In practice, however, it is computationally involved and even impossible to handle such a tremendous amount of moment conditions. I now discard the assumption of Gaussian disturbances and simplify Assumption 3.2.1 as follows:

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[1] One potential issue is that some high-order moment conditions may be redundant. The technique of relevant moment selection can be used to accommodate redundancy, see Hall and Peixe (2003), Hall *et al.* (2007, 2012), Cheng and Liao (2015) for details.

Assumption 3.2.2. *$\eta_i \sim i.i.d.(0, \sigma_\eta^2)$ and $\varepsilon_{it} \sim i.i.d.(0, \sigma_\varepsilon^2)$, η_i and ε_{it} are mutually independent across i.*

Under Assumption 3.2.2, only second moment conditions are available, which are stated as the quadratic expectation of $u_{it} = (1-\rho)\,\eta_i + \varepsilon_{it}$:

$$\mathbb{E}\left(u_{it}u_{is} - \sigma_\eta^2\right) = \mathbb{E}\left[(y_{it} - \alpha y_{i,t-1})(y_{is} - \alpha y_{i,s-1}) - \sigma_\eta^2\right] = 0 \tag{3.2}$$

$$\mathbb{E}\left(u_{it}^2 - \sigma_\eta^2 - \sigma_\nu^2\right) = \mathbb{E}\left[(y_{it} - \alpha y_{i,t-1})^2 - \sigma_\eta^2 - \sigma_\nu^2\right] = 0 \tag{3.3}$$

where the subscripts in the above two equations satisfy: Eq.(3.2): $s = 2, \cdots, t-1$; $t = 3, \cdots, T$; Eq.(3.3): $t = 2, \cdots, T$. Hence, the number of moment conditions in Eq.(3.2) is $(T-1)(T-2)/2$, while the number of moment conditions in Eq.(3.3) is $(T-1)$.

The framework in this paper can also be applied to more complicated models with nonlinear dynamic relationship or non-standard disturbance. The use of the additional nonlinear moment conditions not only promotes the asymptotic efficiency of the linear GMM estimators, but also automatically estimates the variance parameters σ_η^2 and σ_ν^2. It is straightforward to prove that under some regularity conditions, the nonlinear GMM estimator is consistent and asymptotically normally distributed.

The moment conditions in (3.2) and (3.3) can be re-expressed in a more compact manner:

$$\mathbb{E}\left[\left(Z_{1i}' - \alpha Z_{1i,-1}'\right)(Y_i - \alpha Y_{i,-1}) - \sigma_\eta^2 \iota_1\right] = 0 \tag{3.4}$$

$$\mathbb{E}\left[\left(Z_{2i}' - \alpha Z_{2i,-1}'\right)(Y_i - \alpha Y_{i,-1}) - \sigma_\eta^2 \iota_2 - \sigma_\nu^2 \iota_2\right] = 0 \tag{3.5}$$

where Z_{1i} is a $(T-1) \times (T-1)(T-2)/2$ matrix given by:

$$Z_{1i} = \begin{bmatrix} y_{i3} & \cdots & y_{iT} & 0 & \cdots & 0 & \cdots & 0 & 0 & 0 \\ 0 & \cdots & 0 & y_{i4} & \cdots & y_{iT} & \cdots & 0 & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & 0 & \cdots & 0 & \cdots & y_{i,T-1} & y_{iT} & 0 \\ 0 & \cdots & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & y_{iT} \\ 0 & \cdots & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & 0 \end{bmatrix}; \tag{3.6}$$

Z_{2i} is a $(T-1)\times(T-1)$ matrix given by:

$$Z_{2i} = \begin{bmatrix} y_{i2} & 0 & \cdots & 0 \\ 0 & y_{i3} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & y_{iT} \end{bmatrix}; \tag{3.7}$$

Y_i is a $(T-1)\times 1$ vector defined as $Y_i = (y_{i2}, y_{i3}, \cdots, y_{iT})'$; $Z_{1i,-1}$, $Z_{2i,-1}$, and $Y_{i,-1}$ are the first order lagged matrices of Z_{1i}, Z_{2i}, and Y_i, respectively; ι_1 and ι_2 are a vector of ones with dimensions $(T-1)(T-2)/2\times 1$ and $(T-1)\times 1$, respectively.

Let $Z_i = (Z_{1i}, Z_{2i})$, then the moment conditions (3.4) and (3.5) can be written more succinctly as:

$$\mathbb{E}\left[\left(Z_i' - \alpha Z_{i,-1}'\right)\left(Y_i - \alpha Y_{i,-1}\right) - \sigma_\eta^2 \begin{pmatrix} \iota_1 \\ \iota_2 \end{pmatrix} - \sigma_\nu^2 \begin{pmatrix} \iota_3 \\ \iota_2 \end{pmatrix}\right] = 0. \tag{3.8}$$

The number of moment conditions is $T(T-1)/2$, which is also the column dimension of matrix Z_i.

3.3 Weak Identification and Finite Sample Bias

In this section, I first provide a theoretical argument that the nonlinear moment conditions substantially alleviate the weak identification problem arising in dynamic panels where the autoregressive parameters are near-unity, or the variance of individual effect is large with respect to the variance of idiosyncratic error. I then analytically explore the bias of both linear and nonlinear GMM estimators, and show that nonlinear moments serve to reduce bias in linear GMM estimation.

3.3.1 The Problem of Weak Identification: Linear v.s. Nonlinear Moments

As an illustration, I consider the dynamic panel model (3.1) over $T = 3$ time periods. Applying the first-difference transformation to (3.1) yields

$$\Delta y_{i3} = \alpha \Delta y_{i2} + \Delta \nu_{i3} \tag{3.9}$$

where Δy_{i2} is an endogenous variable. As discussed in Section 2.1, one possible linear moment condition is $\mathbb{E}\left(y_{i1} \Delta \nu_{i3}\right) = 0$. However, y_{i1} is a weakly correlated with Δy_{i2}, as illustrated in Blundell and Bond (1998). To see this, they consider the first stage equation of 2SLS procedure

$$\Delta y_{i2} = (\alpha - 1)\, y_{i1} + \eta_i + \nu_{i2}. \tag{3.10}$$

It could be shown that the probability limit of the ordinary least square estimator $\hat{\varpi}$ for $\varpi = (\alpha - 1)$ is

$$\text{plim}\hat{\varpi} = (\alpha - 1) \frac{\kappa}{\kappa + \sigma_\eta^2 / \sigma_\nu^2}\,, \quad with \quad \kappa = \frac{1 - \alpha}{1 + \alpha} \geq 0.$$

Thus the bias term scales the estimated coefficient $\hat{\varpi}$ on the instrumental variable y_{i1} towards zero. The probability limit of $\hat{\varpi}$ converges to zero ($\text{plim}\hat{\varpi} \to 0$) in two different scenarios: (i) the autoregressive parameter of the observable data y approaches 1: $\alpha \to 1$; (ii) the variance of individual fixed effect is extremely larger than the variance of idiosyncratic error: $\sigma_\eta^2 \gg \sigma_\nu^2$, i.e., the variance ratio tends to infinity: $\sigma_\eta^2 / \sigma_\nu^2 \to \infty$.

I next discuss how the use of the nonlinear moments overcomes the problem of weak instrumentation. Note that the nonlinear moments in (3.3) include $\mathbb{E}\left(u_{i3}^2 - \sigma_\eta^2 - \sigma_\nu^2\right) = 0$ and $\mathbb{E}\left(u_{i2}^2 - \sigma_\eta^2 - \sigma_\nu^2\right) = 0$. Differencing these two moments yields $\mathbb{E}\left[\left(u_{i3} + u_{i2}\right) \Delta \nu_{i3}\right] = 0$, which implies that $\left(u_{i3} + u_{i2}\right)$ satisfies the exogeneity conditions. To verify that $\left(u_{i3} + u_{i2}\right)$ can serve as an appropriate instrumental variable, it suffices to show $\mathbb{E}\left[\left(u_{i3} + u_{i2}\right) \Delta y_{i2}\right] \neq 0$.

Case 1: unit root in the dependent variable, i.e., $\alpha = 1$.

In this case, model (3.1) is reduced to $\Delta y_{it} = \eta_i + \nu_{it}$, from which one obtains

$$\mathbb{E}\left[\left(u_{i3} + u_{i2}\right) \Delta y_{i2}\right] = \mathbb{E}\left[\left(2\eta_i + \nu_{i3} + \nu_{i2}\right)\left(\eta_i + \nu_{i2}\right)\right] = 2\sigma_\eta^2 + \sigma_\nu^2 \neq 0$$

Case 2: infinite variance ratio, i.e., $\sigma_\eta^2/\sigma_\nu^2 \to \infty$.

If the autoregressive parameter $\alpha \neq 1$, then

$$\mathbb{E}\left[\left(u_{i3}+u_{i2}\right)\Delta y_{i2}\right] = \mathbb{E}\left[\left(\nu_{i3}+\nu_{i2}\right)\left(\left(\alpha-1\right)y_{i1}+\eta_i+\nu_{i2}\right)\right] = \sigma_\nu^2 \neq 0,$$

which does not depend on the variance ratio given $\sigma_\nu^2 \neq 0$.

Interestingly, when $\alpha = 1$, a large variance ratio indicates that $(u_{i3}+u_{i2})$ is a strong instrument. As shown in Case 1, it is helpful to note that

$$\mathbb{E}\left[\left(u_{i3}+u_{i2}\right)\Delta y_{i2}\right] = \sigma_\nu^2\left(2\times\frac{\sigma_\eta^2}{\sigma_\nu^2}+1\right) \to \infty.$$

Thus, in unit root panels where the variance ratio is extremely high, the relatively large σ_η^2 compared to σ_ν^2 implies that the instrumental variable $(u_{i3}+u_{i2})$ is strongly correlated with the endogenous variable Δy_{i2}. Moreover, it can be proved that the concentration parameter μ^2, which measures the strength of the instruments at a formal level (Rothenberg, 1984; Stock and Yogo, 2005), is exactly a monotonically increasing function of the variance ratio in this case.

3.3.2 Relative Bias via Stochastic Power-series Expansion

In the preceding section, I show that the number of moment conditions may increase sharply by exploiting the nonlinear information of the unknown parameters. The inclusion of these nonlinear moment conditions significantly improves the asymptotic efficiency of the GMM estimator in the sense that they introduce additional strong information for identification. It is of great interest to examine whether the nonlinear moment conditions are beneficial to bias reduction in addition to efficiency improvement. One may suspect that the nonlinear GMM estimator may suffer from severe finite sample bias due to the classical problem of many moments. Nevertheless, the nonlinear GMM estimator outperforms the standard linear ones based on finite sample bias comparison, as revealed by following deduction and later simulation studies.

In panel models, deriving an explicit expression for the bias term is technically challenging, especially when the model has a complex representation. The problem is fundamentally more difficult in my framework because of the nonlinearity involved in estimation and the lack of a closed-form solution. Here I continue to use the above setup and formally demonstrate how the nonlinear GMM estimator generates a smaller finite sample bias by using stochastic power-series expansion.

Consider a simultaneous equation model with a single endogenous variable Δy_{i2} and a single instrumental variable y_{i1}:

$$\Delta y_{i3} = \alpha \Delta y_{i2} + \Delta \nu_{i3}$$
$$\Delta y_{i2} = (\alpha - 1)\, y_{i1} + \eta_i + \nu_{i2}.$$

To simplify the notations, I write $w_i = (\alpha - 1)\, y_{i1}$, $\xi_{it} = \eta_i + \nu_{i2}$ and $\zeta_{it} = \Delta \nu_{i3}$, where $\xi_{it} \sim i.i.d.(0, \sigma_\xi^2)$ and $\zeta_{it} \sim i.i.d.(0, \sigma_\zeta^2)$. By definition, the concentration parameter can be written as $\mu^2 = W'W/\sigma_\xi^2$, where $W = (w_1, w_2, \cdots, w_N)'$. Rothenberg (1984) proposes the following standardized two-stage least squares estimator

$$\frac{\sqrt{W'W}}{\sigma_\zeta}\left(\hat{\alpha}_{2sls} - \alpha\right) = \frac{\sqrt{W'W}}{\sigma_\zeta} \frac{W'\zeta + \xi' P_{\mathcal{Y}} \zeta}{W'W + 2W'\xi + \xi' P_{\mathcal{Y}} \xi} = \frac{U_\zeta + (S_{\xi\zeta}/\mu)}{1 + (2U_\xi/\mu) + (S_{\xi\xi}/\mu^2)}$$

where $P_{\mathcal{Y}} = \mathcal{Y}_1 \left(\mathcal{Y}_1' \mathcal{Y}_1\right)^{-1} \mathcal{Y}_1'$ is the idempotent projection matrix with $\mathcal{Y}_1 = (y_{1,1}, y_{2,1}, \cdots, y_{N,1})'$, U_ζ, U_ξ, $S_{\xi\zeta}$ and $S_{\xi\xi}$ are standardized random variables defined as:

$$U_\zeta = \frac{W'\zeta}{\sigma_\zeta \sqrt{W'W}}\,, \quad U_\xi = \frac{W'\xi}{\sigma_\xi \sqrt{W'W}}\,, \quad S_{\xi\zeta} = \frac{\xi' P_{\mathcal{Y}} \zeta}{\sigma_\zeta \sigma_\xi}\,, \quad S_{\xi\xi} = \frac{\xi' P_{\mathcal{Y}} \xi}{\sigma_\xi^2}.$$

Thus, U_ζ and U_ξ are standard normal variables, $S_{\xi\zeta}$ and $S_{\xi\xi}$ are elements of a matrix with a central Wishart distribution. When the concentration parameter μ^2 is large, the standardized estimator behaves like the standard normal variable U_ζ. In this standardized form of the two-stage least squares estimator, μ^2 virtually plays the role similar to the effective sample size (Rothenberg, 1984; Stock and Yogo, 2005). By using the stochastic power-series expansion, we have

$$\frac{\sqrt{W'W}}{\sigma_\zeta}\left(\hat{\alpha}_{2sls} - \alpha\right) = U_\zeta + \frac{S_{\xi\zeta} - 2U_\zeta U_\xi}{\mu} + \frac{4U_\zeta U_\xi^2 - 2U_\xi S_{\xi\zeta} - U_\zeta S_{\xi\xi}}{\mu^2} + O_p\left(\mu^{-3}\right).$$

As shown in the literature (Hahn and Kuersteiner, 2002; Bun and Windmeijer, 2010; Kim and Pohlmeier, 2016), to order $o\left(\mu^{-2}\right)$, the higher-order approximation for the bias of $\hat{\alpha}_{2sls}$ can be expressed as:

$$Bias\left(\hat{\alpha}_{2sls}\right) \approx -\frac{1}{N}\frac{\sigma_{\xi\zeta}}{\sigma_{\xi}^{2}}\frac{1}{\mu_0^2/N}$$

where μ_0 is the probability limit of $\hat{\mu}$ estimated from the first-stage equation.

3.3.2.1 Bias with Linear Moments

When linear moment conditions are used for estimation, we have

$$\frac{\hat{\mu}^2}{N} = \frac{\left[\left(\mathcal{Y}_1'\mathcal{Y}_1\right)^{-1}\mathcal{Y}_1'\Delta\mathcal{Y}_2\right]^2\mathcal{Y}_1'\mathcal{Y}_1/N}{\Delta\mathcal{Y}_2'\left(I-P_{\mathcal{Y}}\right)\Delta\mathcal{Y}_2/N} \rightarrow_p \frac{\left[\mathbb{E}\left(y_{i1}\Delta y_{i2}\right)\right]^2\left[\mathbb{E}\left(y_{i1}^2\right)\right]^{-1}}{\mathbb{E}\left(\Delta y_{i2}^2\right)-\left[\mathbb{E}\left(y_{i1}\Delta y_{i2}\right)\right]^2\left[\mathbb{E}\left(y_{i1}^2\right)\right]^{-1}} \equiv \frac{\mu_0^2}{N}$$

where $\hat{\mu}^2 = \hat{W}'\hat{W}/\hat{\sigma}_{\xi}^2$ is estimated from the first-stage equation.

Under the assumption of covariance stationarity of the initial observation, it is easily verified that

$$\frac{\mu_0^2}{N} = \frac{\left(1-\alpha\right)^2\sigma_{\nu}^2}{\left(1-\alpha^2\right)\sigma_{\nu}^2+2\left(1+\alpha\right)\sigma_{\eta}^2}.$$

This implies that the bias of the linear GMM estimator $\hat{\alpha}_{2sls,l}$ can be well approximated by

$$Bias\left(\hat{\alpha}_{2sls,l}\right) \approx -\frac{1}{N}\frac{Cov\left(\Delta\nu_{i3},\eta_i+\nu_{i2}\right)}{Var\left(\eta_i+\nu_{i2}\right)}\frac{1}{\mu_0^2/N} = \frac{1}{N}\frac{\left(1-\alpha^2\right)+2\left(1+\alpha\right)\sigma_{\eta}^2/\sigma_{\nu}^2}{\left(1-\alpha\right)^2\left(1+\sigma_{\eta}^2/\sigma_{\nu}^2\right)}.$$

Clearly, the bias of $\hat{\alpha}_{2sls,l}$ is a monotonic increasing function of the autoregressive parameter α and the variance ratio $\sigma_{\eta}^2/\sigma_{\nu}^2$. Hence, the severe finite sample bias of the linear GMM estimator is associated with persistent data series or a large variance ratio[2].

[2]In this example, I only discuss the equation in differences with the lagged level variables as an instrument. My results also apply to the equation in levels where the instrument is the lagged differenced variable. In this case, one can obtain an identical expression for the concentration parameter. Similarly, the corresponding bias can be shown to increase as the autoregressive parameter or the variance ratio grows. Therefore, the equation in levels also suffers from the weak instrument problem in dynamic panels with persistent dependent variable or a large variance ratio.

3.3.2.2 Bias with Nonlinear Moments

As discussed earlier, when the nonlinear moment conditions are included, it is equivalent to using $(u_{i3} + u_{i2})$ as an additional instrument. Recall that the error term $(\eta_i + \nu_{i2})$ in the first-stage equation is correlated with the instrumental variable y_{i1}. With this in mind, I decompose $(\eta_i + \nu_{i2})$ into an instrumental variable component $(u_{i3} + u_{i2})$ and an exogenous component $(\nu_{i2} - \nu_{i3})$. Hence, the first-stage equation can be expressed as

$$\Delta y_{i2} = (\alpha - 1)\, y_{i1} + \frac{1}{2}\left(u_{i3} + u_{i2}\right) + \frac{1}{2}\left(\nu_{i2} - \nu_{i3}\right).$$

Note that the new error term is $\left(\nu_{i2} - \nu_{i3}\right)/2$, and the coefficient on the instrumental variable component $(u_{i3} + u_{i2})$ is predetermined as $1/2$. Rearranging the first-stage equation, it can be deduced that

$$\begin{aligned}
\frac{\hat{\mu}^2}{N} =& \frac{\left[\left(\mathcal{Y}_1'\mathcal{Y}_1\right)^{-1}\mathcal{Y}_1'\left(\Delta\mathcal{Y}_2 - u_3/2 - u_2/2\right)\right]^2 \mathcal{Y}_1'\mathcal{Y}_1/N}{\left(\Delta\mathcal{Y}_2 - u_3/2 - u_2/2\right)'\left(I - P_{\mathcal{Y}}\right)\left(\Delta\mathcal{Y}_2 - u_3/2 - u_2/2\right)/N} \\
\rightarrow_p& \frac{\left[\mathbb{E}\left(y_{i1}\Delta y_{i2} - y_{i1}u_{i3}/2 - y_{i1}u_{i2}/2\right)\right]^2\left[\mathbb{E}\left(y_{i1}^2\right)\right]^{-1}}{\mathbb{E}\left[\left(\Delta y_{i2} - u_{i3}/2 - u_{i2}/2\right)^2\right] - \left[\mathbb{E}\left(y_{i1}\Delta y_{i2} - y_{i1}u_{i3}/2 - y_{i1}u_{i2}/2\right)\right]^2\left[\mathbb{E}\left(y_{i1}^2\right)\right]^{-1}} \equiv \frac{\mu_0^2}{N}.
\end{aligned}$$

Since

$$\frac{\mu_0^2}{N} = \frac{2\left(1 - \alpha\right)}{1 + \alpha} + 2\frac{\sigma_\eta^2}{\sigma_\nu^2},$$

the bias of the nonlinear GMM estimator $\hat{\alpha}_{2sls,n}$ behaves approximately as

$$Bias\left(\hat{\alpha}_{2sls,n}\right) \approx -\frac{1}{N}\frac{Cov\left(\Delta\nu_{i3}, \left(\nu_{i2} - \nu_{i3}\right)/2\right)}{Var\left(\left(\nu_{i2} - \nu_{i3}\right)/2\right)}\frac{1}{\mu_0^2/N} = \frac{1}{N}\left(\frac{1-\alpha}{1+\alpha} + \frac{\sigma_\eta^2}{\sigma_\nu^2}\right)^{-1}.$$

Combining the results above, one can obtain the approximate relative bias of the nonlinear GMM estimator versus the linear GMM estimator

$$\begin{aligned}
RelaBias\left(\hat{\alpha}_{2sls}\right) &= Bias\left(\hat{\alpha}_{2sls,n}\right)/Bias\left(\hat{\alpha}_{2sls,l}\right) \\
&\approx \frac{\left(1-\alpha\right)^2\left(1 + \sigma_\eta^2/\sigma_\nu^2\right)}{\left[\left(1-\alpha\right)/\left(1+\alpha\right) + \sigma_\eta^2/\sigma_\nu^2\right]\left[\left(1-\alpha^2\right) + 2\left(1+\alpha\right)\sigma_\eta^2/\sigma_\nu^2\right]} \\
&= \frac{\left(1-\alpha\right)^2\left(1 + \sigma_\eta^2/\sigma_\nu^2\right)}{\left(1-\alpha\right)^2\left(1 + \sigma_\eta^2/\sigma_\nu^2\right) + 2\left(1-\alpha^2\right)\sigma_\eta^2/\sigma_\nu^2 + 2\left(1+\alpha\right)\sigma_\eta^4/\sigma_\nu^4} < 1.
\end{aligned}$$

I therefore conclude that the small sample bias of the traditional linear estimator is ultimately reduced by introducing additional nonlinear moment conditions. I will verify this argument in the subsequent Monte Carlo experiments.

3.4 Estimation and Inference

In this section, I develop the estimation and inference method based on the nonlinear moment conditions. I also present a generalization of my procedure to allow for higher order autocorrelation and time-varying heterogeneity in the error terms.

3.4.1 Algorithm and Asymptotic Properties

Before investigating possible extensions, I first present the procedure for nonlinear GMM estimation in dynamic panels with white noise errors. The same algorithm can be easily adapted to cases of more complex error structures.

Specifically, define the moment function

$$g_i(\theta) = \left(Z_i' - \alpha Z_{i,-1}'\right)(Y_i - \alpha Y_{i,-1}) - \sigma_\eta^2 \iota_a - \sigma_\nu^2 \iota_b$$

where $\iota_a' = (\iota_1', \iota_2')$, and $\iota_b' = (0', \iota_2')$. The nonlinear moment conditions can be written as $\mathbb{E}[g_i(\theta)] = 0$, where $\theta = \left(\alpha, \sigma_\eta^2, \sigma_\nu^2\right)'$ is a vector of unknown parameters. The nonlinear GMM estimator is achieved by minimizing the following criterion function

$$\hat{\theta}_{ngmm} = \arg\min_{\theta\in\Theta} \mathcal{Q}_N(\theta) = \arg\min_{\theta\in\Theta} \bar{g}_N(\theta)' W_N \bar{g}_N(\theta) \tag{3.11}$$

where $\bar{g}_N(\theta) = N^{-1}\sum_{i=1}^N g_i(\theta)$, and W_N is some weight matrix. As there is no closed-form solution to this nonlinear optimization problem, I employ the iterative Gauss-Newton algorithm to derive the nonlinear GMM estimator. I start with the linearization of the sample moment function $\bar{g}_N(\theta)$, which is obtained by taking the first order Taylor expansion of $\bar{g}_N(\theta)$ around $\hat{\theta}_j$

$$\bar{g}_N(\theta) \cong \bar{g}_N\left(\hat{\theta}_j\right) + G_N\left(\hat{\theta}_j\right)\left(\theta - \hat{\theta}_j\right) = v_j - G_j\theta \tag{3.12}$$

where $v_j \equiv \bar{g}_N\left(\hat{\theta}_j\right) - G_N\left(\hat{\theta}_j\right)\hat{\theta}_j$, $G_j \equiv -G_N\left(\hat{\theta}_j\right)$, and $G_N(\theta) \equiv \partial\bar{g}_N(\theta)/\partial\theta'$. To be concrete, we have

$$\begin{cases} G_j = \left(G_{j\alpha}, \iota_a, \iota_b\right) \\ v_j = \left[Z'Y - \hat{\alpha}_j^2 Z'_{-1}Y_{-1}\right]/N \end{cases}$$

where $G_{j\alpha} = \left[\left(Z'Y_{-1} + Z'_{-1}Y\right) - 2\hat{\alpha}_j Z'_{-1}Y_{-1}\right]/N$, $Z' = \left(Z'_1, Z'_2, \cdots, Z'_N\right)$ is a $T(T-1)/2 \times N(T-1)$ matrix, $Y' = \left(Y'_1, Y'_2, \cdots, Y'_N\right)$ is a $N(T-1) \times 1$ column vector, Z_{-1} and Y_{-1} are the first order lagged matrices of Z and Y, respectively.

Replacing the sample moment function by its linearized form (3.12), the original optimization problem (3.11) is reduced to minimizing the quadratic function

$$\hat{\theta}_{j+1} = \arg\min_{\theta\in\Theta} \mathcal{Q}_j(\theta) = \arg\min_{\theta\in\Theta} \left(v_j - G_j\theta\right)' W_N \left(v_j - G_j\theta\right). \tag{3.13}$$

Thus, the iterative approximation of the nonlinear GMM estimator based on the Gauss-Newton algorithm is given by:

$$\hat{\theta}_{j+1} = \left(G'_j W_N G_j\right)^{-1} G'_j W_N v_j = \hat{\theta}_j + \left(G'_j W_N G_j\right)^{-1} G'_j W_N \bar{g}_N(\hat{\theta}_j) \tag{3.14}$$

which will converge to the solution $\hat{\theta}_{ngmm}$ to (3.11).

Under some regularity conditions, it can be shown that $\hat{\theta}_{ngmm}$ is a consistent estimator and has an asymptotically normal distribution

$$\sqrt{N}\Omega^{-\frac{1}{2}}\left(\hat{\theta}_{ngmm} - \theta_0\right) \to_d \mathcal{N}\left(0, I_N\right)$$

where Ω is the asymptotic variance-covariance matrix of the optimally weighted nonlinear GMM estimator.

It is important to notice that the DGP of the dynamic panel data model (3.1) involves certain constraints on the unknown parameters: $|\alpha|, |\rho| < 1$, and $\sigma_\eta^2, \sigma_\nu^2 > 0$. Thus, one could incorporate these information into the GMM estimation by reparameterization:

$$\begin{aligned} \alpha &= \frac{\exp(\delta_1) - 1}{\exp(\delta_1) + 1}, \quad -\infty < \delta_1 < +\infty \\ \sigma_\eta^2 &= \exp(\delta_2), \quad -\infty < \delta_2 < +\infty \\ \sigma_\nu^2 &= \exp(\delta_3), \quad -\infty < \delta_3 < +\infty. \end{aligned} \tag{3.15}$$

In the transformed model, the vector of unknown parameters $\delta = (\delta_1, \delta_2, \delta_3)'$ satisfies $\theta = \hbar(\delta)$, where $\hbar(\cdot)$ is a continuous function. Given $\hat{\delta} \to_p \delta_0$ and $\sqrt{N}\left(\hat{\delta} - \delta_0\right) \to_d \mathcal{N}(0, V)$, it is straightforward to show that

$$\sqrt{N}\left(\hat{\theta} - \theta_0\right) \to_d \mathcal{N}\left[0, \left(\partial\hbar(\delta_0)/\partial\hat{\delta}'\right) V \left(\partial\hbar(\delta_0)/\partial\hat{\delta}'\right)'\right] \tag{3.16}$$

where $\hat{\theta} = \hbar\left(\hat{\delta}\right)$, $\theta_0 = \hbar(\delta_0)$, and $\frac{\partial\hbar(\delta_0)}{\partial\hat{\delta}'} = \left.\frac{\partial\hbar(\hat{\delta})}{\partial\hat{\delta}'}\right|_{\hat{\delta}=\delta_0}$.

3.4.2 Extensions to AR(p) and MA(q) Errors

I next consider extensions of my framework to dynamic panels with AR(p) and MA(q) errors, where $p, q \geqslant 1$. In the case where the idiosyncratic errors ν_{it} follow an AR(p) process, we have

$$\nu_{it} = \sum_{s=1}^{p} \rho_s \nu_{i,t-s} + \varepsilon_{it}.$$

Assumption 3.2.2 implies the following nonlinear moments:

$$\begin{aligned} \mathbb{E}\left(u_{it}u_{is} - \sigma_\eta^2 - \gamma_{\nu,|t-s|}\right) &= \mathbb{E}\left[(y_{it} - \alpha y_{i,t-1})(y_{is} - \alpha y_{i,s-1}) - \sigma_\eta^2 - \gamma_{\nu,|t-s|}\right] = 0 \\ \mathbb{E}\left(u_{it}^2 - \sigma_\eta^2 - \sigma_\nu^2\right) &= \mathbb{E}\left[(y_{it} - \alpha y_{i,t-1})^2 - \sigma_\eta^2 - \sigma_\nu^2\right] = 0 \end{aligned}$$

where $\gamma_{\nu,j}$ is the jth autocovariance of ν_{it}.

Similarly, for MA(q) errors

$$\nu_{it} = \sum_{s=0}^{q} \rho_s \varepsilon_{i,t-s}, \quad with \quad \rho_0 = 1,$$

one can construct the corresponding nonlinear moments as follows

$$\mathbb{E}\left(u_{it}u_{is} - \sigma_\eta^2 - \sum_{r=0}^{q-|t-s|} \rho_r \rho_{r+|t-s|}\sigma_\varepsilon^2\right) = 0\ , \quad \mathbb{E}\left(u_{it}^2 - \sigma_\eta^2 - \sum_{r=0}^{q} \rho_r^2 \sigma_\varepsilon^2\right) = 0,$$

where $u_{it} = y_{it} - \alpha y_{i,t-1}$. Except for the increased number of unknown parameters, the estimation and inference procedure is similar to that discussed in Section 4.1. To choose the optimal lag length in the error term, one can adopt the shrinkage method, such as Lasso, for model selection and parameter estimation.

3.4.3 Time-varying Heterogeneity

My approach also applies suitably to the setting in which the idiosyncratic errors exhibit time-varying heterogeneity. To illustrate, consider the standard first-order dynamic panel data model with white noise errors. Suppose that the disturbances are heteroskedastic over time, i.e., $Var\left(\nu_{it}\right) = \sigma_{\nu,t}^2$. The nonlinear moments for this model satisfy:

$$\mathbb{E}\left(u_{it}u_{is} - \sigma_\eta^2\right) = \mathbb{E}\left[\left(y_{it} - \alpha y_{i,t-1}\right)\left(y_{is} - \alpha y_{i,s-1}\right) - \sigma_\eta^2\right] = 0 \tag{3.17}$$

$$\mathbb{E}\left(u_{it}^2 - \sigma_\eta^2 - \sigma_{\nu,t}^2\right) = \mathbb{E}\left[\left(y_{it} - \alpha y_{i,t-1}\right)^2 - \sigma_\eta^2 - \sigma_{\nu,t}^2\right] = 0. \tag{3.18}$$

On the other hand, to detect the time-dependent heterogeneity in the error component, one can test the following null hypothesis

$$H_0 : \sigma_{\nu,1}^2 = \sigma_{\nu,2}^2 = \cdots = \sigma_{\nu,T}^2.$$

The corresponding Wald statistic has an asymptotic chi-squared distribution with degree of freedom $(T-1)$.

3.5 Monte Carlo Simulations

In this section, I evaluate the finite-sample behavior of the nonlinear GMM estimator through a series of simulation experiments and compare its performance to that of the standard linear (difference and system) GMM estimators.

3.5.1 Design

In the simulations, the data are generated from the following linear dynamic panel data model

$$y_{it} = \alpha y_{i,t-1} + \eta_i + \nu_{it} \tag{3.19}$$

where $i = 1, 2, \cdots, N$, $t = 2, 3, \cdots, T$, $\eta_i \sim i.i.d.\mathcal{N}\left(0, \sigma_\eta^2\right)$, $\nu_{it} \sim i.i.d.\mathcal{N}\left(0, \sigma_\nu^2\right)$, η_i and ν_{it} are independently distributed across i. The initial observation of the dependent variable is specified as

$$y_{i1} = \frac{\eta_i}{1-\alpha} + \frac{\nu_{i1}}{\sqrt{1-\alpha^2}}.$$

To investigate how the estimators work under different parameterizations, I choose different values for the autoregressive parameter α in model (3.19): $\alpha \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$. The variances of η_i and ν_{it} are set at $\left(\sigma_\eta^2, \sigma_\nu^2\right) \in \{(1,4), (1,1), (4,1)\}$. For each specification of α and $\left(\sigma_\eta^2, \sigma_\nu^2\right)$, I consider sample sizes with $N \in \{50, 100\}$ and $T \in \{5, 10\}$, which gives rise to 60 combinations in total. In addition, the number of simulation replications is 1,000.

3.5.2 Results

Figure 3.1 presents the finite sample bias and RMSE of the nonlinear GMM estimator for the autoregressive parameter α relative to that of the linear (difference and system) GMM estimators. The main findings are summarized as follows. First, as shown by the bars, the relative bias is far less than 1 under most parameterizations and sample sizes considered. This provides corroborative evidence that including nonlinear moment conditions substantially alleviates the bias problem in linear GMM estimation. Note that when $T = 5$, the nonlinear GMM estimator does not always outperform the system GMM estimator in the presence of relatively small persistence parameter and variance ratio, e.g., $\alpha = 0.1$, $\sigma_\eta^2/\sigma_\nu^2 = 1/4$. In general, the bias reduction is more pronounced as T increases, but becomes less substantial as α moves closer to 0 or $\sigma_\eta^2/\sigma_\nu^2$ gets smaller.

Second, I observe that the relative bias of the nonlinear GMM estimator is smaller with respect to the difference GMM estimator than the system GMM estimator in virtually all cases. In other words, the nonlinear moment conditions reduce the bias more successfully in difference GMM estimation than system GMM estimation. This is in line with various simulation studies in the literature pointing to the relatively better performance of the system GMM estimator compared to the difference GMM estimator when the mean stationarity assumption is satisfied.

Finally, in terms of relative RMSE, which is plotted as dots in Figure 3.1, I see a similar improvement resulting from the use of nonlinear moment conditions. Specifically, the nonlinear GMM estimator has a smaller RMSE than the linear GMM estimators in almost all scenarios, suggesting that the additional nonlinear information ensures the stability of the GMM estimator.

To present a more clear visualization, I plot the kernel smoothing density function of the linear and nonlinear GMM estimators for α in Figure 3.2-Figure 3.4. For brevity, I only report the results for cases where $N = 100$, $\sigma_\eta^2/\sigma_\nu^2 \in \{1/4, 4\}$, $\alpha \in \{0.1, 0.5, 0.9\}$. Compared to the linear GMM estimators, the nonlinear GMM estimator generally has smaller bias and variance, and more closely approximates a normal distribution. However, some exception to this emerge when T, α and $\sigma_\eta^2/\sigma_\nu^2$ are relatively small. For example, when $T = 5$, $\alpha = 0.1$ and $\sigma_\eta^2/\sigma_\nu^2 = 1/4$, the distributions of the system and nonlinear GMM estimators almost completely overlap. The mean of both estimators is sufficiently close to the true value, though the bias of the system GMM estimator is slightly smaller. As T, α or $\sigma_\eta^2/\sigma_\nu^2$ increases, the nonlinear GMM estimator performs clearly better than the linear ones. In cases of high persistence and large variance ratio, only the nonlinear GMM estimator appears to be normally distributed and has a reasonably small bias.

Overall, the simulation results demonstrate that the nonlinear GMM estimator proposed in this paper dominates the conventional linear GMM estimators in terms of finite sample performance. There is also evidence that the nonlinear moments may provide researchers with a useful tool to deal with the weak instrument problem in dynamic panel models in the context of highly persistent series or a large variance ratio.

3.6 Empirical Illustration

In this section, I apply my method to estimation of value-added models with learning dynamics. To implement the empirical analysis, I specify the model as follows (see Andrabi et al., 2011; Verdier, 2016)

$$y_{it} = \alpha y_{i,t-1} + \beta T_{it} + \gamma' x_{it} + \eta_i + \nu_{it} \tag{3.20}$$

where y_{it} is the academic achievement of student i in year t, T_{it} is the teacher, classroom or school indicator variable, x_{it} is a vector that contains student-level or classroom-level characteristics, and η_i is the unobserved student ability. The autoregressive parameter α measures the level of persistence in learning, and β captures the contribution of T_{it} to educational production. The long-term effect of T_{it} is given by $\beta/(1-\alpha)$.

Conventional value-added models often assume that student achievement perfectly persists between years or grades, i.e., $\alpha = 1$. Model (3.20) then reduces to a static panel

$$\triangle y_{it} = \beta T_{it} + \gamma' x_{it} + \eta_i + \nu_{it}.$$

When the assumption of perfect learning persistence is violated, the resulting estimates from this simplified specification are likely to be quite misleading. This has motivated researchers to include lagged achievement in the model as an important input to current performance. However, when the true learning persistence is high, the traditional linear GMM estimators tend to severely underestimate α as suggested by the theoretical argument and simulation evidence in previous sections. In this case, one might mistakenly attribute the effect of past educational input to the effect of T_{it}. The advocated nonlinear GMM estimation strategy thus serves as a stepping stone to provide more accurately estimated treatment effect β.

I first estimate the effect of class size on student academic performance using the data from Project STAR. The STAR experiment was conducted in the state of Tennessee beginning from the school year 1985-1986. In this project, kindergarten students and their teachers in each participating school were randomly assigned to small or regular-sized class. Students were required to remain in the same class type through grade 3. A more thorough discussion of Project STAR can be found in Krueger (1999) and Chetty et al. (2011). In this exercise, the academic outcomes are measured by the student's percentile scores in reading and math, and the treatment is constructed as a dummy variable for whether the student was assigned to a small class. I control for the same set of variables for student and teacher characteristics as in Krueger (1999). I estimate the model using both the system and nonlinear GMM estimators. The results are reported in Table 3.1. The first two columns present the estimated persistence and the estimated class size effect on the average percentile scores. As can be seen, all coefficients are positive and statistically significant at the 1% level. The system GMM estimator produces a persistence parameter of 0.513 and a class size parameter of 7.416. Adding nonlinear moments raises the estimated learning persistence by 31% while reduces the estimated class size effect by 28.6%. In addition, the nonlinear GMM estimator returns a higher long-run impact of class size reduction on student achievement. The results remain largely unchanged when I separately estimate the effect on the percentile rankings in reading and math, as shown in the last four columns.

To provide more evidence, I next assess the importance of private school to education production among students in 3 districts of Punjab in Pakistan. The data I use come from Andrabi et al. (2011), which are part of a longitudinal survey of learning in Pakistan. The survey initially collected information on third graders in the sample villages and followed them for the two subsequent years. In this analysis, I focus on the effect of attending private school on three types of achievement measures: test scores in English, Urdu and math. The tests were graded using Item Response Theory to preserve cardinality of the scale across years. A suite of child and family controls similar to Andrabi et al. (2011) are included in the model. Table 3.2 presents the corresponding results. Again, I find that the inclusion of nonlinear moments leads to estimates of higher learning persistence and smaller effect of private school attendance. The degree of persistence produced by the nonlinear GMM estimator is between 0.5 and 0.7, which resembles closely to that in Table 3.1. In comparison, the persistence coefficient falls to 0.3-0.5 when the system GMM estimator is employed.

3.7 Conclusion

This paper has considered the use of nonlinear moment conditions for estimation and inference in dynamic panel data models. The main idea of the approach is to construct nonlinear moment conditions by exploiting all available high-order moment functions of the error components. I first rigorously develop the results in dynamic panels with white noise errors. I also provide extensions to other settings in which the error structure is of a more complicated form, allowing for higher order autocorrelation and time-varying heterogeneity. This generalization is important for applied economic studies where researcher have prior information that heteroskedasticity is present and not negligible. More importantly, I show that the resulting nonlinear GMM estimator is robust to the weak identification problem arising from linear GMM estimation in cases where the autoregressive parameter moves close to unit root or the variance ratio diverges to infinity. The simulation findings indicate that the proposed nonlinear GMM estimator has better finite sample performance than the linear GMM estimators. It also appears to perform well in empirical settings with highly persistent data series. The results in this paper suggest that the nonlinear GMM estimation procedure may provide a useful complement to the currently proposed strategies for reducing bias in dynamic panel modelling.

Tables and Figures

Table 3.1 Estimation Results for Class Size Effect in the STAR Program

	Average percentile score		Percentile reading score		Percentile math score	
	LSGMM	NLGMM	LSGMM	NLGMM	LSGMM	NLGMM
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged score	0.513***	0.672***	0.501***	0.618***	0.366***	0.521***
	(0.026)	(0.018)	(0.025)	(0.018)	(0.025)	(0.017)
Small class	7.416***	5.517***	7.518***	6.302***	9.584***	7.869***
	(0.599)	(0.500)	(0.629)	(0.547)	(0.676)	(0.562)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Long-term Effects	15.22***	16.81***	15.05***	16.48***	15.12***	16.44***
	(0.958)	(1.247)	(1.022)	(1.213)	(0.914)	(1.016)
Observations	13,091	13,091	12,840	12,840	13,013	13,013

Notes: Standard errors in parentheses. The control variables are similar to those in Krueger (1999), including student race, student gender, free lunch dummy, teacher race, years of teaching experience, and highest degree of teacher. The average percentile score is reported for students with only reading score or math score.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

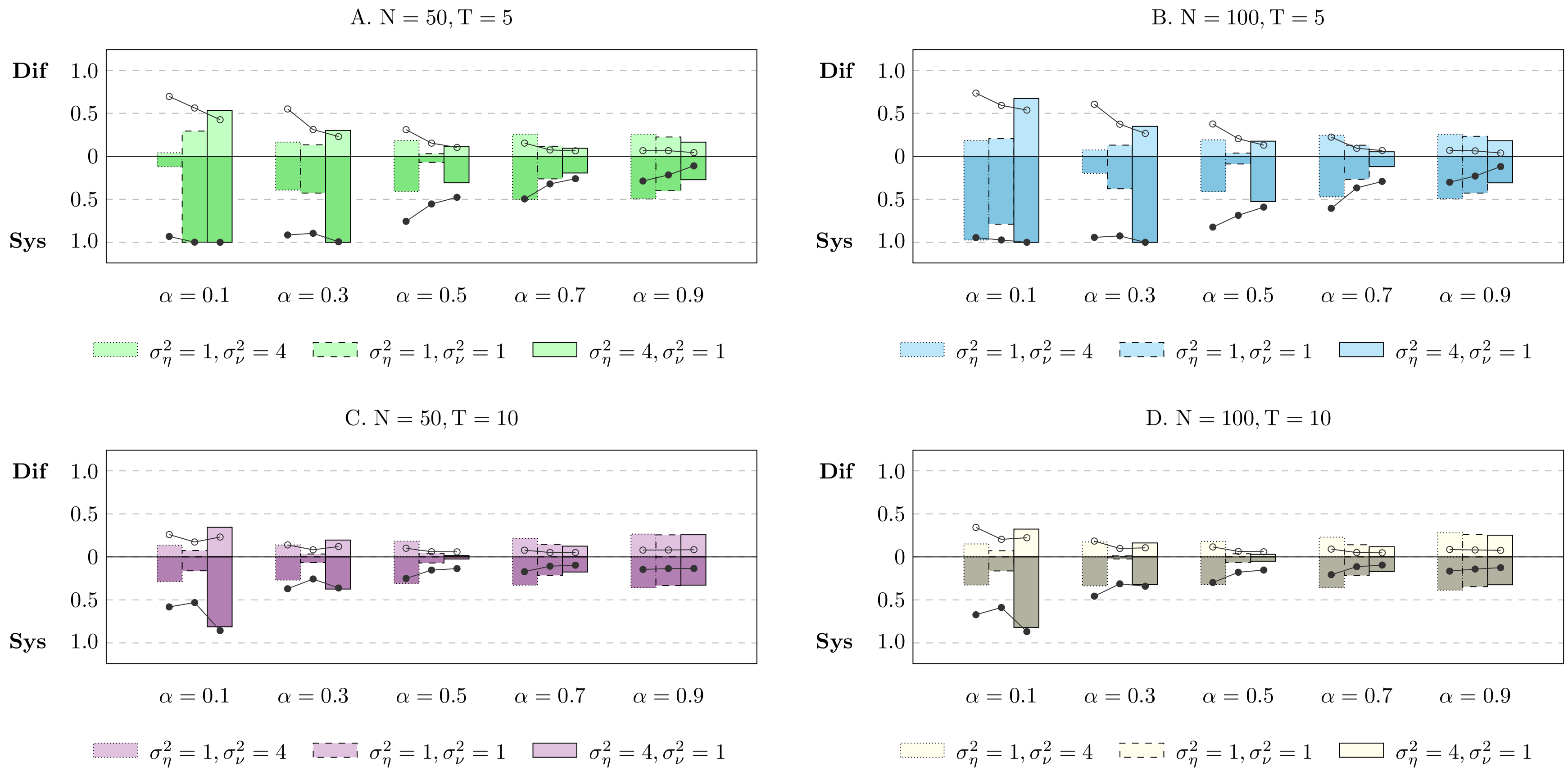
Table 3.2 Estimation Results for Private School Effect with Pakistani Survey Data

	English score		Urdu score		Math score	
	LSGMM	NLGMM	LSGMM	NLGMM	LSGMM	NLGMM
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged score	0.366***	0.544***	0.461***	0.663***	0.471***	0.600***
	(0.020)	(0.018)	(0.020)	(0.018)	(0.021)	(0.019)
Private school	0.434***	0.285***	0.306***	0.183***	0.281***	0.219***
	(0.020)	(0.019)	(0.018)	(0.017)	(0.019)	(0.018)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Long-term Effects	0.683***	0.624***	0.567***	0.542***	0.532***	0.548***
	(0.022)	(0.027)	(0.027)	(0.039)	(0.033)	(0.039)
Observations	14,152	14,152	14,169	14,169	14,180	14,180

Notes: Standard errors in parentheses. The control variables are similar to those in Andrabi et al. (2011), including child age, child gender, child schooling measured by years of study, number of elder brothers living together, number of elder sisters living together, child height score, child weight score, child asset wealth index, mother education, father education, whether the mother lives at home, whether the father lives at home, and survey date.

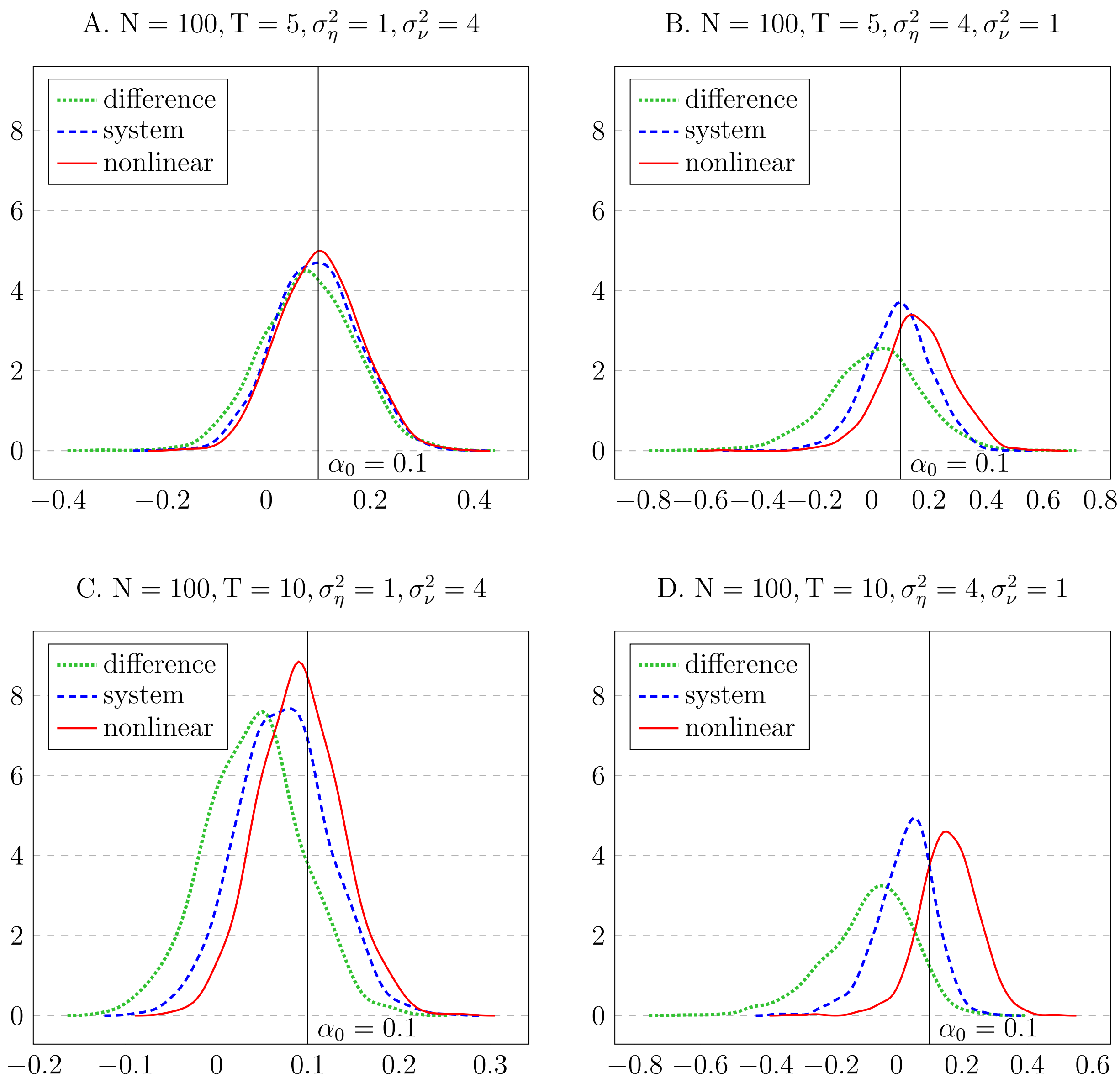
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 3.1 Simulation Results for Relative Bias and Relative RMSE



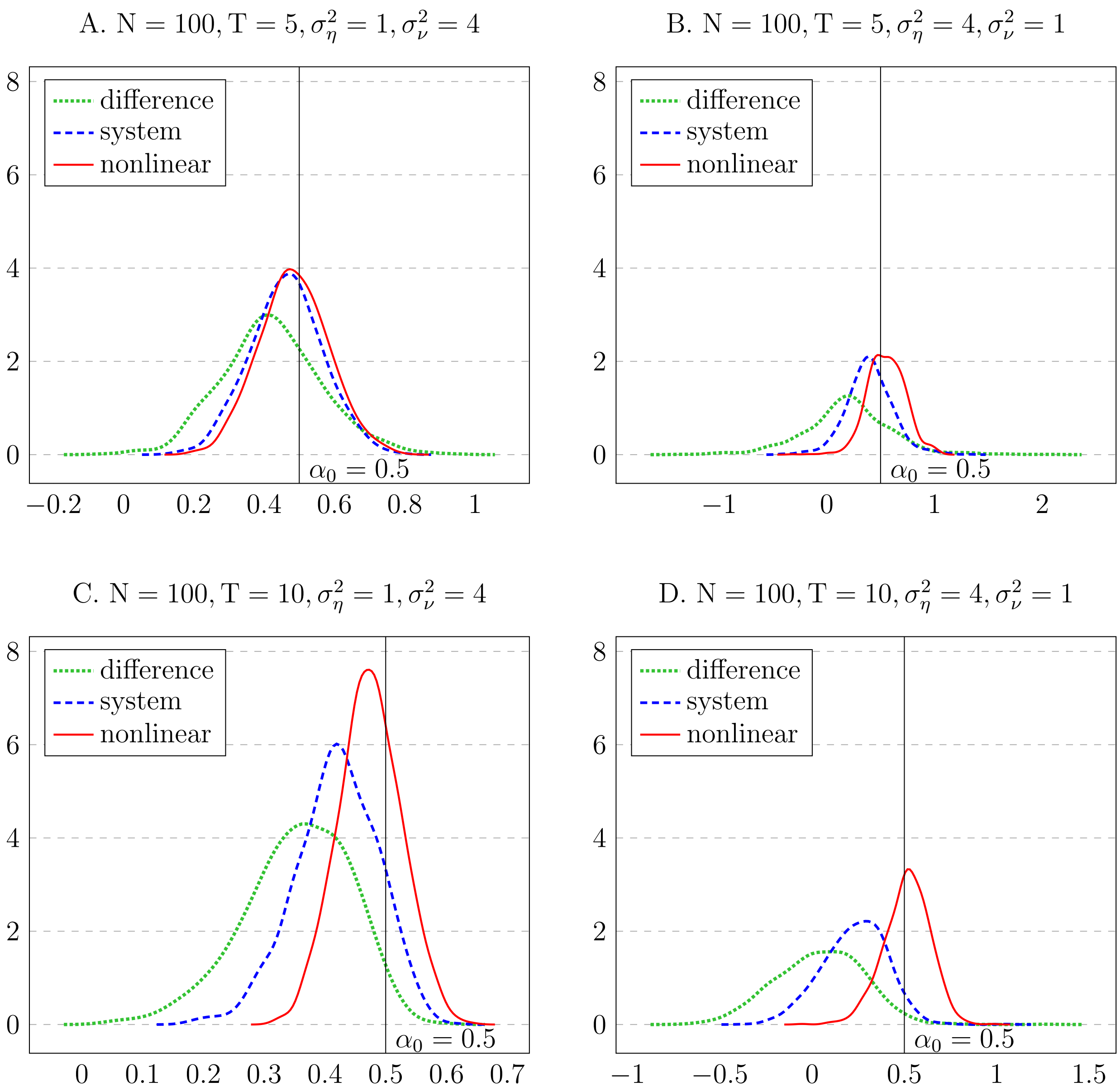
Notes: This figure shows the finite sample relative bias (marked as bars) and relative RMSE (marked as dots) of the nonlinear GMM estimator for the autoregressive parameter α relative to that of the linear (difference and system) GMM estimators. The bars and dots above the zero horizontal line depict the relative bias/RMSE as apposed to the difference GMM estimator, while those below the zero horizontal line represent the relative bias/RMSE with respect to the system GMM estimator. To make the figure concise, I shrink the relative ratio to 1 when the number is larger than 1, i.e., the performance of the linear GMM estimator is better than the nonlinear one. The variances of η_i and ν_{it} are specified as $(\sigma_\eta^2, \sigma_\nu^2) \in \{(1,4),(1,1),(4,1)\}$. For each specification of α and $(\sigma_\eta^2, \sigma_\nu^2)$, I consider sample sizes with $N \in \{50, 100\}$, $T \in \{5, 10\}$, and the number of simulation replications is 1,000.

Figure 3.2 Kernel Smoothing Density Functions for GMM Estimators of α ($\alpha_0 = 0.1$)



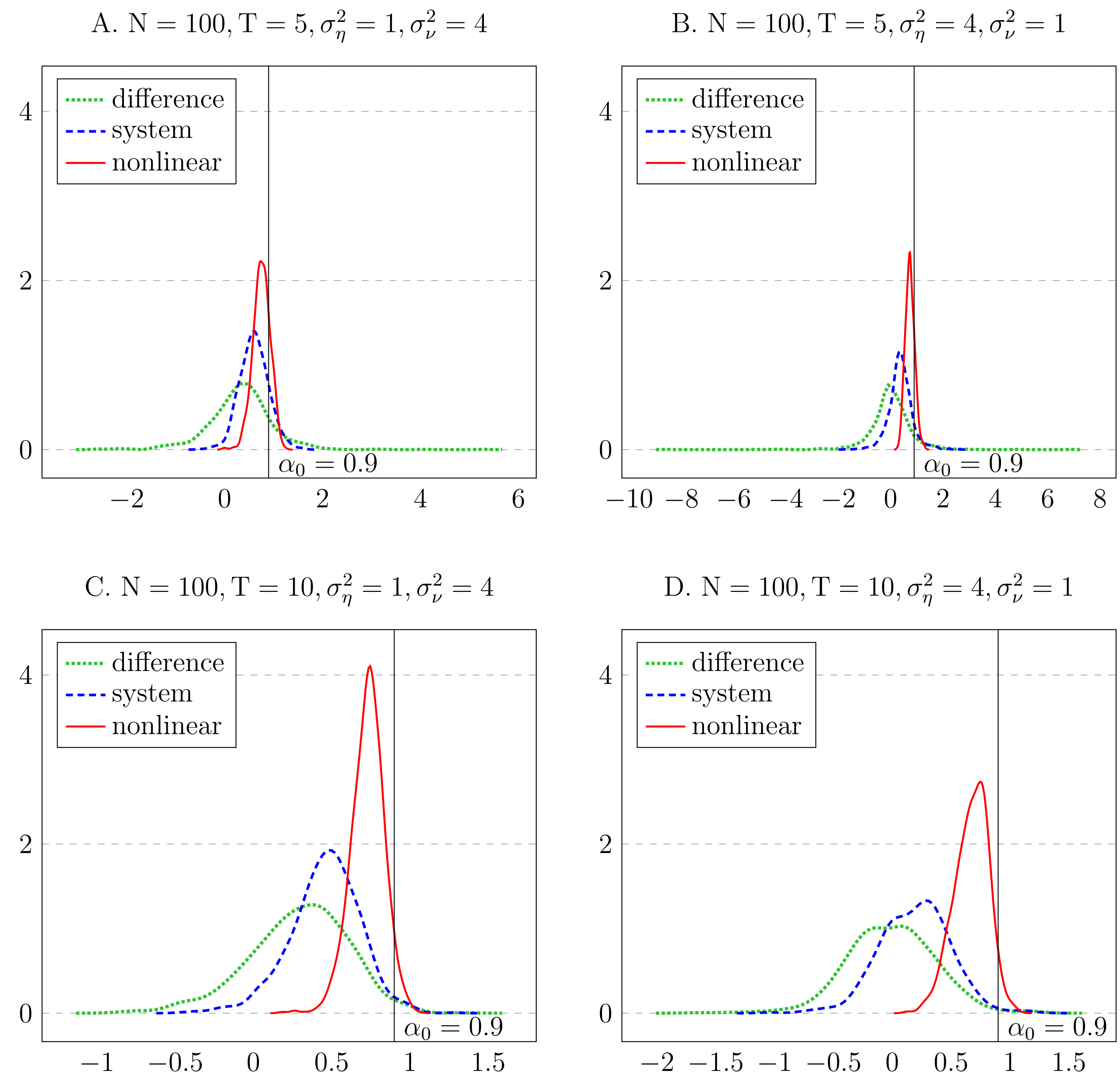
Notes: This figure shows the kernel smoothing density function of the linear and nonlinear GMM estimators for α in the settings with true value $\alpha_0 = 0.1$. I plot the distributions for the difference, system and nonlinear GMM estimators. The values in y-axis represent the density, while those in the x-axis represent the value of α. The variances of η_i and ν_{it} are specified as $\left(\sigma_\eta^2, \sigma_\nu^2\right) \in \{(1,4),(4,1)\}$. For each specification of $\left(\sigma_\eta^2, \sigma_\nu^2\right)$, I consider sample sizes with $N = 100$, $T \in \{5, 10\}$, and the number of simulation replications is 1,000.

Figure 3.3 Kernel Smoothing Density Functions for GMM Estimators of α ($\alpha_0 = 0.5$)



Notes: This figure shows the kernel smoothing density function of the linear and nonlinear GMM estimators for α in the settings with true value $\alpha_0 = 0.5$. I plot the distributions for the difference, system and nonlinear GMM estimators. The values in y-axis represent the density, while those in the x-axis represent the value of α. The variances of η_i and ν_{it} are specified as $\left(\sigma_\eta^2, \sigma_\nu^2\right) \in \{(1,4),(4,1)\}$. For each specification of $\left(\sigma_\eta^2, \sigma_\nu^2\right)$, I consider sample sizes with $N = 100$, $T \in \{5, 10\}$, and the number of simulation replications is 1,000.

Figure 3.4 Kernel Smoothing Density Functions for GMM Estimators of α ($\alpha_0 = 0.9$)



Notes: This figure shows the kernel smoothing density function of the linear and nonlinear GMM estimators for α in the settings with true value $\alpha_0 = 0.9$. I plot the distributions for the difference, system and nonlinear GMM estimators. The values in y-axis represent the density, while those in the x-axis represent the value of α. The variances of η_i and ν_{it} are specified as $(\sigma_\eta^2, \sigma_\nu^2) \in \{(1,4),(4,1)\}$. For each specification of $(\sigma_\eta^2, \sigma_\nu^2)$, I consider sample sizes with $N = 100$, $T \in \{5, 10\}$, and the number of simulation replications is 1,000.

Bibliography

Abadie, A. and Cattaneo, M. D. (2018). Econometric methods for program evaluation. *Annual Review of Economics*, 10(1):465–503.

Ahn, S. C. and Schmidt, P. (1995). Efficient estimation of models for dynamic panel data. *Journal of Econometrics*, 68(1):5–27.

Alonso-Borrego, C. and Arellano, M. (1999). Symmetrically normalized instrumental-variable estimation using panel data. *Journal of Business & Economic Statistics*, 17(1):36–49.

Anderson, S. and Eswaran, M. (2009). What determines female autonomy? Evidence from Bangladesh. *Journal of Development Economics*, 90(2):179–191.

Anderson, S. and Ray, D. (2010). Missing women: Age and disease. *The Review of Economic Studies*, 77(4):1262–1300.

Anderson, T. and Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. *Journal of Econometrics*, 18(1):47–82.

Andrabi, T., Das, J., Khwaja, A. I., and Zajonc, T. (2011). Do value-added estimates add value? Accounting for learning dynamics. *American Economic Journal: Applied Economics*, 3(3):29–54.

Angrist, J. (2002). How do sex ratios affect marriage and labor markets? Evidence from America's second generation. *The Quarterly Journal of Economics*, 117(3):997–1038.

Angrist, J. D., Graddy, K., and Imbens, G. W. (2000). The interpretation of instrumental variables estimators in simultaneous equations models with an application to the demand for fish. *The Review of Economic Studies*, 67(3):499–527.

Angrist, J. D. and Imbens, G. W. (2009). *Mostly Harmless Econometrics: An Empiricists Companion*. Princeton University Press, Princeton.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2):277–297.

Attané, I., Qunlin, Z., Shuzhuo, L., Xueyan, Y., and Guilmoto, C. Z. (2013). Bachelorhood and sexuality in a context of female shortage: Evidence from a survey in rural anhui, china. *The China Quarterly*, 215:703726.

Balke, A. and Pearl, J. (1997). Bounds on treatment effects from studies with imperfect compliance. *Journal of the American Statistical Association*, 92(439):1171–1176.

Banister, J. (2004). Shortage of girls in china today. *Journal of Population Research*, 21(1):19–45.

Becker, G. (1981). *A Treatise on the Family Cambridge MA*. Harvard University Press, Cambridge, MA.

Becker, G. S. (1965). A Theory of the Allocation of Time. *The Economic Journal*, 75(299):493–517.

Becker, G. S. (1985). Human capital, effort, and the sexual division of labor. *Journal of Labor Economics*, 3(1, Part 2):S33–S58.

Beegle, K., Weerdt, J. D., and Dercon, S. (2011). Migration and economic mobility in tanzania: Evidence from a tracking survey. *The Review of Economics and Statistics*, 93(3):1010–1033.

Bertrand, M., Cortés, P., Olivetti, C., and Pan, J. (2016). Social norms, labor market opportunities, and the marriage gap for skilled women. Working Paper Series 22015, National Bureau of Economic Research.

Bisin, A. and Topa, G. (2003). Empirical models of cultural transmission. *Journal of the European Economic Association*, 1(2-3):363–375.

Bisin, A. and Verdier, T. (2000). “Beyond the melting pot”: Cultural transmission, marriage, and the evolution of ethnic and religious traits. *The Quarterly Journal of Economics*, 115(3):955–988.

Bisin, A. and Verdier, T. (2001). The economics of cultural transmission and the dynamics of preferences. *Journal of Economic Theory*, 97(2):298–319.

Bittman, M., Rice, J. M., and Wajcman, J. (2004). Appliances and their impact: The ownership of domestic technology and time spent on household work. *The British Journal of Sociology*, 55(3):401–423.

Black, S. E. and Devereux, P. J. (2011). Recent developments in intergenerational mobility. In *Handbook of Labor Economics*, volume 4, chapter 16, pages 1487–1541. Elsevier.

Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, 87(1):115–143.

Booth, A. L. and Kee, H. J. (2009). Intergenerational transmission of fertility patterns. *Oxford Bulletin of Economics and Statistics*, 71(2):183–208.

Bound, J., Jaeger, D. A., and Baker, R. M. (1995). Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *Journal of the American statistical association*, 90(430):443–450.

Boustan, L. P. and Collins, W. J. (2014). The origin and persistence of black-white differences in women’s labor force participation. In *Human capital in history: The American record*, pages 205–240. University of Chicago Press.

Browning, M. and Chiappori, P. A. (1998). Efficient intra-household allocations: A general characterization and empirical tests. *Econometrica*, 66(6):1241–1278.

Bun, M. and Kleibergen, F. (2013). Identification and inference in moments based analysis of linear dynamic panel data models. *University of Amsterdam-Econometrics Discussion Paper*, 7.

Bun, M. J. and Windmeijer, F. (2010). The weak instrument problem of the system gmm estimator in dynamic panel data models. *The Econometrics Journal*, 13(1):95–126.

Bun, M. J. and Windmeijer, F. (2011). A comparison of bias approximations for the two-stage least squares (2sls) estimator. *Economics Letters*, 113(1):76–79.

Busso, M., DiNardo, J., and McCrary, J. (2009). Finite sample properties of semiparametric estimators of average treatment effects. Working paper.

Bütikofer, A. (2013). Revisiting 'mothers and sons' preference formation and the female labor force in switzerland. *Labour Economics*, 20:82–91.

Cameron, L., Meng, X., and Zhang, D. (2017). China's sex ratio and crime: Behavioural change or financial necessity? *The Economic Journal*, forthcoming.

Cardia, E. (2008). Household technology: Was it the engine of liberation? In *2008 Meeting Papers*, number 826. Society for Economic Dynamics.

Chen, X. (2017). Does daughter deficit promote parental substance use? Longitudinal evidence on smoking from rural china. IZA Discussion Papers 10860, Institute of Labor Economics (IZA).

Chen, Y., Li, H., and Meng, L. (2013). Prenatal sex selection and missing girls in china: Evidence from the diffusion of diagnostic ultrasound. *Journal of Human Resources*, 48(1):36–70.

Chetty, R., Friedman, J. N., Hilger, N., Saez, E., Schanzenbach, D. W., and Yagan, D. (2011). How does your kindergarten classroom affect your earnings? evidence from project star. *The Quarterly journal of economics*, 126(4):1593–1660.

Chiang, Y.-L., Hannum, E., and Kao, G. (2015). Its not just about the money: Gender and youth migration from rural china. *Chinese Sociological Review*, 47(2):177–201.

Cigno, A. (2007). A theoretical analysis of the effects of legislation on marriage, fertility, domestic division of labour, and the education of children.

Cigno, A. (2012). Marriage as a commitment device. *The Review of Economics of the Household*, 10(2):193–213.

Cigno, A., Komura, M., and Luporini, A. (2017). Self-enforcing family rules, marriage and the (non) neutrality of public intervention. *Journal of Population Economics*, 30(3):805–834.

Coen-Pirani, D., Len, A., and Lugauer, S. (2010). The effect of household appliances on female labor force participation: Evidence from microdata. *Labour Economics*, 17(3):503–513.

Corak, M. (2013). Income inequality, equality of opportunity, and intergenerational mobility. *Journal of Economic Perspectives*, 27(3):79–102.

Cruz, L. M. and Moreira, M. J. (2005). On the validity of econometric techniques with weak instruments inference on returns to education using compulsory school attendance laws. *Journal of Human Resources*, 40(2):393–410.

de V. Cavalcanti, T. V. and Tavares, J. (2008). Assessing the engines of liberation: Home appliances and female labor force participation. *The Review of Economics and Statistics*, 90(1):81–88.

Ding, P., Feller, A., and Miratrix, L. (2019). Decomposing treatment effect variation. *Journal of the American Statistical Association*, 114(525):304–317.

Dinkelman, T. (2011). The effects of rural electrification on employment: New evidence from south africa. *American Economic Review*, 101(7):3078–3108.

Dittmer, L. and Liu, G. (2006). *Chinas Deep Reform: Domestic Politics in Transition.* Rowman & Littlefield Publishers.

Djebbari, H. and Smith, J. (2008). Heterogeneous impacts in PROGRESA. *Journal of Econometrics*, 145(1):64 – 80.

Doepke, M. and Tertilt, M. (2016). Families in Macroeconomics. In *Handbook of Macroeconomics*, volume 2, chapter 2, pages 1789–1891. Elsevier.

Doepke, M. and Zilibotti, F. (2008). Occupational Choice and the Spirit of Capitalism*. *The Quarterly Journal of Economics*, 123(2):747–793.

Dohmen, T., Falk, A., Huffman, D., and Sunde, U. (2012). The intergenerational transmission of risk and trust attitudes. *The Review of Economic Studies*, 79(2):645–677.

Duflo, E. and Udry, C. (2004). Intrahousehold resource allocation in cote d'ivoire: Social norms, separate accounts and consumption choices. Working Paper Series 10498, National Bureau of Economic Research.

Ebenstein, A. (2010). The missing girls of china and the unintended consequences of the one child policy. *Journal of Human Resources*, 45(1):87–115.

Ebenstein, A. and Sharygin, E. J. (2016). Demographic change, prostitution, and sexually transmitted infection rates in china. pages 437–461.

Ebenstein, A. Y. and Sharygin, E. J. (2009). The consequences of the missing girls of china. *World Bank Economic Review*, 23(3):399–425.

Edlund, L., Li, H., Yi, J., and Zhang, J. (2007). Sex ratios and crime: Evidence from China's one-child policy. IZA Discussion Papers 3214.

Edlund, L., Li, H., Yi, J., and Zhang, J. (2013). Sex ratios and crime: Evidence from China. *The Review of Economics and Statistics*, 95(5):1520–1534.

Edmonds, E. V. (2006). Understanding sibling differences in child labor. *Journal of Population Economics*, 19(4):795–821.

Eika, L., Mogstad, M., and Zafar, B. (2014). Educational assortative mating and household income inequality. Working Paper Series 20271, National Bureau of Economic Research.

Fafchamps, M. and Wahba, J. (2006). Child labor, urban proximity, and household composition. *Journal of Development Economics*, 79(2):374 – 397. Special Issue in honor of Pranab Bardhan.

Fan, J. (2019). Internal geography, labor mobility, and the distributional impacts of trade. *American Economic Journal: Macroeconomics*, 11(3):252–88.

Farré, L. and Vella, F. (2013). The intergenerational transmission of gender role attitudes and its implications for female labour force participation. *Economica*, 80(318):219–247.

Fernández, R. (2013). Cultural change as learning: The evolution of female labor force participation over a century. *American Economic Review*, 103(1):472–500.

Fernández, R., Fogli, A., and Olivetti, C. (2004). Mothers and sons: Preference formation and female labor force dynamics. *The Quarterly Journal of Economics*, 119(4):1249–1299.

Fernández, R., Guner, N., and Knowles, J. (2005). Love and money: A theoretical and empirical analysis of household sorting and inequality. *The Quarterly Journal of Economics*, 120(1):273–344.

Fogli, A. and Veldkamp, L. (2011). Nature or nurture? Learning and the geography of female labor force participation. *Econometrica*, 79(4):1103–1138.

Frey, B. S. and Stutzer, A. (2002). What can economists learn from happiness research? *Journal of Economic Literature*, 40(2):402–435.

Gellatly, C. (2009). Trends in population sex ratios may be explained by changes in the frequencies of polymorphic alleles of a sex ratio gene. *Evolutionary Biology*, 36(2):190–200.

Gong, J., Lu, Y., and Song, H. (2018). The effect of teacher gender on students academic and noncognitive outcomes. *Journal of Labor Economics*, 36(3):743–778.

Greenwood, J., Guner, N., and Vandenbroucke, G. (2017). Family economics writ large. *Journal of Economic Literature*, 55(4):1346–1434.

Greenwood, J., Seshadri, A., and Yorukoglu, M. (2005). Engines of liberation. *The Review of Economic Studies*, 72(1):109–133.

Grier, K. B., Hicks, D. L., and Yuan, W. (2016). Marriage market matching and conspicuous consumption in China. *Economic Inquiry*, 54(2):1251–1262.

Gu, B., Wang, F., Guo, Z., and Zhang, E. (2007). China's local and national fertility policies at the end of the twentieth century. *Population and Development Review*, 33(1):129–147.

Gupta, M. D. (2005). Explaining Asia's "missing women": A new look at the data. *Population and Development Review*, 31(3):529–535.

Hahn, J. and Hausman, J. (2002). A new specification test for the validity of instrumental variables. *Econometrica*, 70(1):163–189.

Hahn, J. and Kuersteiner, G. (2002). Discontinuities of weak instrument limiting distributions. *Economics Letters*, 75(3):325–331.

Hansen, C. and Kozbur, D. (2014). Instrumental variables estimation with many weak instruments using regularized jive. *Journal of Econometrics*, 182(2):290–308.

Hardee-Cleaveland, K. and Banister, J. (1988). Fertility policy and implementation in china, 1986-88. *Population and Development Review*, 14(2):245–286.

Hayakawa, K. and Qi, M. (2020). Further results on the weak instruments problem of the system gmm estimator in dynamic panel data models. *Oxford Bulletin of Economics and Statistics*, 82(2):453–481.

Heath, R. and Tan, X. (2018). Worth fighting for: Daughters improve their mothers' autonomy in south asia. *Journal of Development Economics*, 135:255–271.

Heath, R. and Tan, X. (2019). Intrahousehold bargaining, female autonomy, and labor supply: Theory and evidence from india. *Journal of the European Economic Association*.

Heckman, J. J., Smith, J., and Clements, N. (1997). Making the most out of programme evaluations and social experiments: Accounting for heterogeneity in programme impacts. *The Review of Economic Studies*, 64(4):487–535.

Heckman, J. J. and Vytlacil, E. (2005). Structural equations, treatment effects, and econometric policy evaluation1. *Econometrica*, 73(3):669–738.

Hirano, K., Imbens, G. W., and Ridder, G. (2003). Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica*, 71(4):1161–1189.

Hoel, J. (2013). What causes inefficiency between spouses? A within-subject structural test of the relative importance of asymmetric information and limited contracting with experimental evidence from kenya.

Holtz-Eakin, D., Newey, W., and Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica*, pages 1371–1395.

Horney, J., Osgood, D. W., and Marshall, I. H. (1995). Criminal careers in the short-term: Intra-individual variability in crime and its relation to local life circumstances. *American Sociological Review*, 60(5):655–673.

Hudson, V. M. and Boer, A. D. (2002). A surplus of men, a deficit of peace: Security and sex ratios in asia's largest states. *International Security*, 26(4):5–38.

Imai, K., Keele, L., and Tingley, D. (2010). A general approach to causal mediation analysis. *Psychological methods*, 15(4):309–334.

Imbens, G. W. and Rubin, D. B. (1997). Estimating outcome distributions for compliers in instrumental variables models. *The Review of Economic Studies*, 64(4):555–574.

Iversen, T. and Rosenbluth, F. (2006). The political economy of gender: Explaining cross-national variation in the gender division of labor and the gender voting gap. *American Journal of Political Science*, 50(1):1–19.

Jiang, Q., Zhang, Y., and Sánchez-Barricarte, J. J. (2015). Marriage expenses in rural China. *China Review*, 15(1):207–236.

Jin, X., Liu, L., Li, Y., Feldman, M. W., and Li, S. (2013). 'Bare branches' and the marriage market in rural China: Preliminary evidence from a village-level survey. *Chinese sociological review*, 46(1):83–104.

Johnston, D. W., Schurer, S., and Shields, M. A. (2014). Maternal gender role attitudes, human capital investment, and labour supply of sons and daughters. *Oxford Economic Papers*, 66(3):631–659.

Kawaguchi, D. and Miyazaki, J. (2009). Working mothers and sons preferences regarding female labor supply: Direct evidence from stated preferences. *Journal of Population Economics*, 22(1):115–130.

Kim, N. and Pohlmeier, W. (2016). A note on the regularized approach to biased 2SLS estimation with weak instruments. *Oxford Bulletin of Economics and Statistics*, 78(6):915–924.

Kitagawa, T. (2015). A test for instrument validity. *Econometrica*, 83(5):2043–2063.

Kitazawa, Y. (2001). Exponential regression of dynamic panel data models. *Economics Letters*, 73(1):7–13.

Kohler, H.-P., Rodgers, J. L., and Christensen, K. (1999). Is fertility behavior in our genes? Findings from a danish twin study. *Population and Development Review*, 25(2):253–288.

Krueger, A. B. (1999). Experimental estimates of education production functions. *The quarterly journal of economics*, 114(2):497–532.

Lee, Y. and Okui, R. (2012). Hahn–hausman test as a specification test. *Journal of Econometrics*, 167(1):133–139.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, 30(1):67–80.

Lewis, W. A. (1954). Economic development with unlimited supplies of labour. *Manchester School*, 22(2):139–191.

Li, J. and Cooney, R. S. (1993). Son preference and the one child policy in China: 1979-1988. *Population Research and Policy Review*, 12(3):277–296.

Li, S., Jiang, Q., and Feldman, M. W. (2014). The male surplus in China's marriage market: Review and prospects. In *Analysing China's Population*, pages 77–93. Springer.

Lina, S. (1999). *The Role of Women in Labour Migration: A Case Study in Northern China*, pages 69–89. Palgrave Macmillan UK, London.

Lu, M. and Xia, Y. (2016). Migration in the people's republic of China. Working Paper 593, ABDI.

Lundberg, S. and Pollak, R. A. (1993). Separate spheres bargaining and the marriage market. *Journal of Political Economy*, 101(6):988–1010.

MacKinnon, D. P., Lockwood, C. M., Hoffman, J. M., West, S. G., and Sheets, V. (2002). A comparison of methods to test mediation and other intervening variable effects. *Psychological methods*, 7(1):83.

Magazzini, L. and Calzolari, G. (2020). Testing initial conditions in dynamic panel data models. *Econometric Reviews*, 39(2):115–134.

Mazur, A. and Michalek, J. (1998). Marriage, Divorce, and Male Testosterone. *Social Forces*, 77(1):315–330.

Morrill, M. S. and Morrill, T. (2013). Intergenerational links in female labor force participation. *Labour Economics*, 20:38 – 47.

Morten, M. (2019). Temporary migration and endogenous risk sharing in village India. *Journal of Political Economy*, 127(1):1–46.

Munshi, K. and Rosenzweig, M. (2016). Networks and misallocation: Insurance, migration, and the rural-urban wage gap. *American Economic Review*, 106(1):46–98.

Murphy, M. (2013). Cross-national patterns of intergenerational continuities in childbearing in developed countries. *Biodemography and social biology*, 59(2):101–126.

Olivetti, C., Patacchini, E., and Zenou, Y. (2013). Mothers, friends and gender identity. Working Paper Series 19610, National Bureau of Economic Research.

Raphael, S. (2013). International migration, sex ratios, and the socioeconomic outcomes of nonmigrant mexican women. *Demography*, 50(3):971–991.

Robins, J. M., Rotnitzky, A., and Zhao, L. P. (1994). Estimation of regression coefficients when some regressors are not always observed. *Journal of the American Statistical Association*, 89(427):846–866.

Robinson, J. (2012). Limited insurance within the household: Evidence from a field experiment in kenya. *American Economic Journal: Applied Economics*, 4(4):140–64.

Roland, G. (2004). Understanding institutional change: Fast-moving and slow-moving institutions. *Studies in comparative international development*, 38(4):109–131.

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and statistics*, 71(1):135–158.

Rose, E. K. and Shem-Tov, Y. (2018). Does incarceration increase crime? Working Paper.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Rothenberg, T. J. (1984). Approximating the distributions of econometric estimators and test statistics. In *Handbook of Econometrics*, volume 2, chapter 15, pages 881–935. Elsevier.

Rubin, D. B. (1978). Bayesian inference for causal effects: The role of randomization. *Annals of Statistics*, 6(1):34–58.

Sasaki, M. (2002). The causal effect of family structure on labor force participation among Japanese married women. *Journal of Human Resources*, 37(2):429–440.

Sen, A. (1990). More than 100 million women are missing. *The New York Review of Books*, 37(20):61–66.

Sen, A. (1992). Missing women. *British Medical Journal*, 304(6827):587–588.

Shen, K., Yan, P., and Zeng, Y. (2016). Coresidence with elderly parents and female labor supply in China. *Demographic Research*, S22(23):645–670.

Solon, G. (1999). Intergenerational mobility in the labor market. In *Handbook of Labor Economics*, volume 3, chapter 29, pages 1761–1800. Elsevier.

Staiger, D. and Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, 65(3):557–586.

Stock, J. and Yogo, M. (2005). *Testing for Weak Instruments in Linear IV Regression*, pages 80–108. Cambridge University Press, New York.

Talhelm, T., Zhang, X., Oishi, S., Shimin, C., Duan, D., Lan, X., and Kitayama, S. (2014). Large-scale psychological differences within china explained by rice versus wheat agriculture. *Science*, 344(6184):603–608.

Todaro, M. P. (1969). A model of labor migration and urban unemployment in less developed countries. *American economic review*, 59(1):138–148.

Trivers, R. L. and Willard, D. E. (1973). Natural selection of parental ability to vary the sex ratio of offspring. *Science*, 179(4068):90–92.

Vandello, J. A. and Cohen, D. (1999). Patterns of individualism and collectivism across the United States. *Journal of personality and social psychology*, 77(2):279.

Verdier, V. (2016). Estimation of dynamic panel data models with cross-sectional dependence: Using cluster dependence for efficiency. *Journal of Applied Econometrics*, 31(1):85–105.

Vernon, V. (2010). Marriage: For love, for money and for time? *The Review of Economics of the Household*, 8(4):433–457.

von Hinke, S., Smith, G. D., Lawlor, D. A., Propper, C., and Windmeijer, F. (2016). Genetic markers as instrumental variables. *Journal of Health Economics*, 45:131–148.

Wei, S.-J. and Zhang, X. (2011a). The competitive saving motive: Evidence from rising sex ratios and savings rates in China. *Journal of Political Economy*, 119(3):511–564.

Wei, S.-J. and Zhang, X. (2011b). Sex ratios, entrepreneurship, and economic growth in the people's republic of China. Working Paper 16800, National Bureau of Economic Research.

Wei, S.-J., Zhang, X., and Liu, Y. (2017). Home ownership as status competition: Some theory and evidence. *Journal of Development Economics*, 127:169–186.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Zhang, J. (2017). The evolution of China's one-child policy and its effects on family outcomes. *Journal of Economic Perspectives*, 31(1):141–60.

Zhao, G. M. (2003). Trafficking of women for marriage in China: Policy and practice. *Criminal Justice*, 3(1):83–102.

Zhao, Y. (1999). Leaving the countryside: Rural-to-urban migration decisions in China. *American Economic Review*, 89(2):281–286.

Zhou, W. (2014). Brothers, household financial markets and savings rate in China. *Journal of Development Economics*, 111:34–47.