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Economic development and intergenerational earnings mobility: Evidence from Taiwan

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Economic Development and Intergenerational Earnings Mobility: Evidence from Taiwan

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Abstract

How economic development affects intergenerational earnings elasticity is not well-documented. In this paper, we estimate intergenerational earnings mobility between fathers and sons in Taiwan during a period of rapid economic development. We apply the two-sample approach developed by Björklund and Jäntti (1997) and find that intergenerational earnings elasticity was around 0.4–0.5 in both the early 1990s and the late 2000s. In addition, we estimate the intergenerational rank association in earnings to have been around 0.3 in both periods. Intergenerational earnings mobility in Taiwan is similar to that in less mobile countries such as the U.S., and it remains stable despite rapid economic development.

“It's harder to climb a ladder when the rungs are farther apart.”

Timothy Noah, *The New Republic*, January 13, 2012

1. Introduction

The persistence of inequality is ubiquitous throughout human history. Nevertheless, economists tend to believe that economic development will eventually reduce inequality. For example, the famous Kuznets curve suggests that cross-sectional inequality will first increase, then decrease, as an economy grows.[1] Another important dimension of inequality is the intergenerational transmission of economic status. However, it is very challenging to estimate intergenerational mobility in developing or newly developed countries, even at only one point in time, because high-quality data providing information on two generations are often unavailable.

Recent literature suggests that there is high intergenerational mobility in the fast-growing Asian Tigers: Korea (Choi and Hong 2011; Ueda 2013; Kim 2017), Singapore (Ng, Shen, and Ho 2009; Ng 2007), and Taiwan (Kan, Li, and Wang 2015; Sun and Ueda 2015). Estimated intergenerational earnings elasticities are around 0.2, which is similar to highly mobile Nordic countries. (See Solon [2002] and Corak [2013] for summaries of cross-country differences in intergenerational income mobility.) However, substantial downward bias likely exists in these small estimated elasticities. In order to have information on two successive generations, many of these studies rely on co-residing father-son pairs. Not only do co-residing father-son pairs not constitute a representative sample (Solon 1992), the sons in these pairs tend to be too young to minimize so-called life-cycle bias (Haider and Solon 2006). Imputation bias is another problem overlooked in the literature.[2] These Asian studies rely on the two-sample approach developed by Björklund and Jäntti (1997) to impute fathers’ missing earnings, but they often do so without appropriate secondary samples and earnings predictors. To minimize imputation bias, especially in a fast-changing economy, both secondary samples and earnings predictors need to be observed at a time when fathers are at their prime working age.

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[1] This traditional view has recently been challenged by many researchers. For example, in his popular book *Capital in the Twenty-First Century*, Piketty (2014) provides substantial historical evidence of long-term inequality and argues that the Kuznets curve is in fact a post-World World II anomaly.

[2] We have coined the term “imputation bias.” However, the importance of comparability between actual fathers and potential fathers has been observed by Björklund and Jäntti (1997), and the implications in a fast-growing economy has been discussed by Kim (2017).

In this paper, we estimate intergenerational earnings mobility between fathers and sons in Taiwan in two periods: 2005–2010 and 1990–1994. The primary samples for sons in this paper are working males aged 35–50 from the Taiwan Social Change Survey (TSCS). The TSCS is a representative repeat cross-sectional survey that has been conducted every year since 1990 to track the profound economic, political, and social changes that were taking place in Taiwan. Importantly, the TSCS provides rich information on the level of education, occupation, and industry of the fathers of survey respondents when the respondents were 15 years old. Our main empirical strategy is the Björklund and Jäntti (1997) two-sample method that utilizes a secondary sample to impute fathers' missing earnings. To avoid potential imputation bias, since the average age of sons is about 40, the secondary sample should be drawn from roughly 25 years earlier, when they were 15, to be consistent with the fathers' information in the primary sample. For the more recent period, 2005–2010, we use working males aged 40–55 from the Survey of Family Income and Expenditure (SFIE) in 1978–1982 as the secondary sample of potential fathers. For the earlier period, 1990–1994, because the microdata are not available, we use average earnings by occupation of household heads from the 1968 and 1970 SFIE government reports as a proxy for fathers' missing earnings. This proxy method is essentially equivalent to using occupations to predict earnings in an unrestricted secondary sample by the Björklund and Jäntti two-sample approach. To quantify potential bias and facilitate comparison between the two periods, we also apply the proxy method to the late 2000s data, using average occupational earnings from the 1981 SFIE government report.

Our estimates show that intergenerational earnings elasticity between fathers and sons in Taiwan has been around 0.4–0.5. These results are robust to a wide range of sensitivity checks, including interval regressions and Poisson regressions. We also estimate rank-rank regressions as proposed by Chetty, Hendren, Kline, and Saez (2014). The rank-rank slope between fathers and sons' earnings percentile ranks is around 0.3. Our results suggest that intergenerational earnings mobility in Taiwan is relatively low and that it is similar to less mobile countries such as the U.K. and the U.S. (Solon 1992; Zimmerman 1992; Björklund and Jäntti 1997; Blanden, Gregg, and Macmillan 2007; Bratsberg et al. 2007; Dearden, Machin, and Reed 1997). Somewhat surprisingly, the estimates from the proxy method for intergenerational earnings mobility are nearly identical in both the early 1990s and the late 2000s. Thus, intergenerational earnings mobility appears to have remained stable even though Taiwan grew from a middle-income economy to a high-income economy and experienced rapid economic and social changes during this period.

This paper contributes to the literature in several important ways. We use carefully chosen representative samples to provide more reliable estimates of intergenerational earnings mobility in Taiwan. As Taiwan and the other Asian Tigers share many similarities, intergenerational mobility in all the Asian Tigers is likely low, and the reports in the literature of high mobility are possibly inaccurate and biased. This paper also adds to the recent literature on trends in intergenerational mobility that deals mainly with developed countries. Taiwan experienced rapid economic growth starting in the 1960s and developed into a high-income economy in less than four decades. We provide interesting evidence on trends in intergenerational mobility in a fast-growing country by reporting on four generations of fathers and sons that cover most of the economic development process in Taiwan.

This paper proceeds as follows. Section 2 reviews the relevant literature, and Section 3 briefly introduces the background in Taiwan. We discuss the TSCS and SFIE datasets in Section 4 and the methodology and regression models in Section 5. Section 6 presents the estimation results, and in Section 7 we state our conclusions.

2. Literature Review

Considering the significance of persistent income inequality, it is surprising that intergenerational earnings mobility did not attract much attention from economists before the seminal work of Solon (1992) and Zimmerman (1992). They find an intergenerational earnings elasticity of around 0.4–0.5 in the U.S. and suggest that the small estimates in the earlier literature are the result of measurement error and non-representative samples. As data with earnings from two generations are often unavailable, Björklund and Jäntti (1997) construct a two-sample estimator that predicts fathers' earnings from a secondary sample and uses these predicted earnings as a generated regressor. The two-sample method allows intergenerational mobility to be estimated for countries without long panel data.

Intergenerational income transmission appears to be stronger in less-developed countries and in countries with more cross-sectional income inequality (Solon 2002; Blanden 2013; Corak 2013; Solon 1999; Bratsberg et al. 2007; Solon 2015). Chetty, Hendren, Kline, and Saez (2014) find a strong correlation between intergenerational income association and cross-sectional inequality across areas within the U.S. as well.

Naturally, there is growing concern that intergenerational income mobility is declining due to the large rise in overall income inequality in the U.S. in recent years (Mayer and Lopoo 2005; Aaronson and Mazumder 2008). Surprisingly, recent studies suggest that intergenerational income mobility in the U.S. has remained stable (Lee and Solon 2009; Chetty, Hendren, Kline, Saez, et al. 2014; Hertz 2007). The literature has not suggested any broad trends in intergenerational mobility in developed countries (Aaronson and Mazumder 2008; Bratberg, Anti Nilsen, and Vaage 2005; Chetty, Hendren, Kline, Saez, et al. 2014; Hertz 2007; Lee and Solon 2009; Lefranc and Trannoy 2005; Lefranc, Ojima, and Yoshida 2014; Mayer and Lopoo 2005; Nicoletti and Ermisch 2007; Pekkala and Lucas 2007; Pekkarinen, Salvanes, and Sarvimäki 2017; Markussen and Røed 2017; Modalsli 2017; Clark and Cummins 2015; Long and Ferrie 2013; Olivetti and Paserman 2015; Xie and Killewald 2013; Fan, Yi, and Zhang 2015; Ferrie 2005). However, the evidence sometimes appears conflicting, perhaps due to the demanding data requirements that these studies face.

The literature on intergenerational mobility in East Asian countries is limited due to data availability problems. Only a handful of studies are available on China (Gong, Leigh, and Meng 2012; Deng, Gustafsson, and Li 2013; Fan, Yi, and Zhang 2015), Japan (Lefranc, Ojima, and Yoshida 2014; Ueda 2009), Korea (Choi and Hong 2011; Ueda 2013; Kim 2017), Singapore (Ng, Shen, and Ho 2009; Ng 2007), and Taiwan (Kan, Li, and Wang 2015; Sun and Ueda 2015). Intergenerational earnings elasticities between fathers and sons appear to be 0.5 or greater in urban China, 0.4 in Japan, and around 0.2 within the Asian Tigers. However, in order to have information on both generations, many studies rely on non-representative samples such as co-residing father-son pairs (Deng, Gustafsson, and Li 2013; Kan, Li, and Wang 2015; Ueda 2013; Ng 2007; Ng, Shen, and Ho 2009; Choi and Hong 2011; Fan, Yi, and Zhang 2015). Not only is sample selection a problem, there could also be substantial life-cycle bias, because the fathers tend to be too old and the sons too young within these pairs (Haider and Solon 2006). For example, the co-residing rate is only about 40% in Taiwan, and such families tend to be relatively poorer (Chu and Yu 2009). Because Kan, Li, and Wang (2015) use a co-residing sample, the average age of sons in their study is only 30. Since Taiwanese men need to complete two to three years of compulsory military service before entering the labor market, these sons are still in the early stages of their careers, and their short-run earnings are not a good proxy for permanent earnings.

The entire Asian literature relies on the Björklund and Jäntti two-sample approach. Although the two-sample approach generally performs well in developed countries, caution is required to implement the methodology correctly in a fast-changing economic environment.[3] One potential problem associated with the two-sample approach, which is rarely recognized in the literature, is imputation bias: The distribution of imputed earnings will not necessarily represent the distribution of true earnings. As the relationships between earnings and their predictors in a fast-growing economy can change rapidly, not just earnings predictors but also the secondary sample need to be drawn from the particular time window when the real fathers were at their prime working age (Kim 2017).[4] However, many studies use current occupations to predict permanent earnings (Gong, Leigh, and Meng 2012; Ueda 2009; Lefranc, Ojima, and Yoshida 2014; Ng 2007; Ng, Shen, and Ho 2009), ignoring the possibility that a person's occupation might change over their life cycle. Moreover, in many studies, the secondary samples come from only a few years earlier than the primary samples, and they may not accurately reflect the labor market for the real fathers (Ueda 2013; Sun and Ueda 2015; Ueda 2009; Kan, Li, and Wang 2015). For example, the primary sample in Sun and Ueda (2015) is from 2004–2008, but the secondary sample is from 1998, only six to ten years earlier. In Kan, Li, and Wang (2015), the secondary sample is from 1978–1988 so that it even overlaps with the primary sample, which is from 1988–2006. (Appendix Table A1 presents a summary of the two Taiwanese studies.)

3. Background in Taiwan

Taiwan has one of the highest population densities in the world. With an area of only 14,000 square miles, Taiwan has a population of more than 23 million people. Taiwan has been growing rapidly since the 1960s, along with the other Asian Tigers. Figure 1 shows real GDP per capita in 2011 Taiwanese dollars (TWD) from 1965–2010.

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[3] Recent studies using administrative data generally agree with studies that have used the two-sample approach. For example, the two-sample estimates for intergenerational elasticities in the U.S. and Sweden reported by Björklund and Jäntti (1997) are very close to estimates that are based on actual earnings from administrative records, as reported by Björklund, Roine, and Waldenström (2012) and Chetty, Hendren, Kline, and Saez (2014).

[4] Kim (2017) uses a secondary sample that better approximates actual fathers' birth cohorts and estimates the intergenerational earnings elasticity in Korea to be around 0.4, which is substantially larger than the previous findings in Choi and Hong (2011) and Ueda (2013). Note that the problem of imputation bias is not unique to the Asian literature, though the magnitude of imputation bias is probably smaller in developed countries. For example, Leigh (2007) and Mendolia and Siminski (2016) impute fathers' earnings by current occupations, due to information limitations in the Australian data.

This doubled about every ten years until 1995. It was only TWD 39,429 (USD 986) in 1965. It increased to TWD 79,658 (USD 2,096) in 1975, TWD 160,128 (USD 4,017) in 1985, and TWD 323,363 (USD 12,207) in 1995.[5] In 2010, real GDP per capita reached TWD 595,811 (USD 18,825). (Purchasing power parity GDP per capita was USD 38,593 in 2010.) Figure 2 shows real GDP growth rates in Taiwan from 1965–2010. Taiwan experienced extremely rapid economic growth prior to 1985. Average growth rates were 10.6% from 1965–1974 and 9.3% from 1975–1984. The average real GDP growth rate was 7.3% in 1990–1994, when Taiwan was still an upper middle-income economy. However, as Taiwan became a high-income economy, average GDP growth rates slowed to 5.1% from 1995–2004 and 4.6% from 2005–2010. The Gini coefficients for disposable household income are presented in Figure 3. Interestingly, the Kuznets curve is not applicable to Taiwan. Inequality appears to decrease at first, but it has been increasing since 1980. The Gini coefficient rises from 0.31 in 1990 to 0.34 in 2010.

Taiwan has also undergone significant political and social changes, starting in the late 1980s. It had been under martial law for more than 38 years, but that was ended in 1987. The parliament (Legislative Yuan), which was elected in 1947 and which was supposed to represent mainland China constituencies, resigned in 1991, and a new parliament was elected in 1992. The first direct presidential election took place in 1996. However, it was not until 2000 that the major opposition party (the Democratic Progressive Party, DPP) won the presidential election for the first time. This ended more than 50 years of hegemony by the former ruling party (the Kuomintang, KMT). Taiwan has become a stable democracy. The 2016 presidential election brought party alternation for the third time and the first female president.

The considerations just discussed suggest that sons in the early 1990s were living and working in a society very different from sons in the late 2000s. Taiwan was still a developing economy with high growth rates and an authoritarian government in the early 1990s. By the late 2000s, Taiwan had become a developed economy with slower growth rates and stable democracy. Cross-sectional inequality also increased

[5] Year 2011 is the base year, in which the GDP deflator equals 100. The USD values are based on the official exchange rates for each year. Figures 1 and 2 are based on data from the Directorate General of Budget, Accounting and Statistics, Executive Yuan, Taiwan. Gini coefficients in Figure 3 are from the 2012 Report on the Survey of Family Income and Expenditure.

substantially during this period. The data in the next section will show the generational differences in labor force composition across the four generations of fathers and sons.

4. Data

In this paper, we use the Taiwan Social Change Survey (TSCS) as our primary sample for the sons in both periods studied, 2005–2010 and 1990–1994. Since the TSCS does not have information on earnings for the participants' fathers, but only earnings predictors for them, we utilize the Survey of Family Income and Expenditure (SFIE) to impute fathers' earnings. We discuss these datasets in detail below.

4.1. The More Recent Period, 2005–2010

As few datasets have information for the earnings of two generations, many studies apply the Björklund and Jäntti two-sample method that imputes fathers' earnings from a secondary sample. Although common earning predictors such as level of education, industry, and occupation are available in most datasets, the data requirements for this approach are still very demanding. Haider and Solon (2006) suggest using earnings from the prime working age, 30–50 years old, for both generations to minimize so-called life-cycle bias. Therefore, while many surveys, for example, ask respondents about their fathers' *current* occupations, we need to know what the fathers' occupations were when they were 30–50 years old, to minimize life-cycle bias in predicted earnings. More importantly, not only may people change occupations, the returns to different occupations may change as well, especially in a fast-growing economy. So the relationship between earnings and their predictors may not remain the same over time. Therefore, to reduce imputation bias (and thus life-cycle bias in imputed earnings), we need for the information on earnings predictors and the fathers' sample to be drawn from the time when the fathers were at prime working age.

In this paper, we use the Taiwan Social Change Survey (TSCS) as our primary sample for sons. The TSCS is a repeated cross-sectional survey, a representative sample of Taiwanese adult individuals aged 18 and above. The survey was first conducted in 1984–1985 as a pilot study. It has been since conducted every year from 1990 to the present. While the TSCS was designed to track social changes, and so it focuses on cultural, social, and political considerations, it does contain information on respondents' earnings and provides relevant earnings predictors for respondents and their fathers.

The earnings measure in the TSCS is pre-tax monthly average earnings (labor income).[6] Moreover, the TSCS asks survey participants what their father's education level, industry, and occupation was *when they were 15 years old*. For the current period, we use the TSCS from 2005, 2007, 2009, and 2010, years in which all of the required information was requested in the survey.[7] Taiwanese men need to serve in the military for two to three years; the average retirement age is also relatively young, around 55–60.[8] As Taiwanese men enter the labor market relatively late and leave it relatively early, we restrict the sample to working males aged 35–50 (born in 1955–1975) with positive reported earnings. Out of 1,653 males aged 35–50, 1,451 of them have information on their father's level of education, industry, and occupation, and 1,360 of them report positive earnings. We also restrict the sample to respondents whose fathers were alive when they were 15. This leads to a sample size of 1,299 in the primary sample of sons.

Since we do not have data on fathers' earnings when the sons were 15 years old, we need another sample to predict fathers' missing earnings. As the average age of sons in the primary sample is 43, the secondary sample of potential fathers should be drawn from about 28 years earlier. We use the Survey of Family Income and Expenditure (SFIE) for 1978–1982, which is repeated cross-sectional data available for every year since 1978. The SFIE is a large representative sample, with more than 15,000 households interviewed each year. The average father-son age difference in the TSCS data is about 31 years, with a standard deviation of 7 years. (However, only the 2007 TSCS asks respondents for their father's age.) This implies that the average age of real fathers would have been around 39–53 when the sons were 15. Therefore, we restrict our secondary sample of potential fathers to male household heads aged 40–55 with positive earnings and information on education levels, industries, and occupations.[9]

[6] From 2005–2010, the earnings variable in the TSCS is recorded in 19 brackets in TWD 10,000 (about USD 300): TWD 1–10,000, TWD 10,001–20,000 ... TWD 190,001–200,000, and two top brackets: TWD 200,001–300,000 and TWD 300,001 and above. For the top bracket, we take TWD 300,000 as respondents' earnings. For the lower brackets, we take mid-points to be respondents' earnings: 5000, 15,000 … 195,000, 250,000. The estimates from interval regressions are reported in Table 10 and 11.

[7] We use two surveys in 2005 and one survey in 2007, 2009, and 2010. The 2010 data are from the sixth round of the TSCS. All other data are from the fifth round of the TSCS. Since the second round of the TSCS, each round lasts for five years, with ten different questionnaires in use. Two random samples of respondents are selected each year to complete two questionnaires. The sample size in each survey is about 2,000 adults (18 and above).

[8] The average self-reported retirement age was 54.9 in 2005 and 56.6 in 2010, based on the Survey on Turnover and Movement of Employees. As some people continue to work after they retire from their primary jobs, the average retirement age based on labor force participation was around 61.

[9] The earnings measure is the sum of the following three sources of labor incomes: wages, net agricultural income, and mixed income that consists of net operation surplus and net professional income.

(We divide annual earnings by 12 to obtain average monthly earnings as in the TSCS.) The sample size is 26,110 in the secondary sample of potential fathers.

The earnings predictors need to be coded in exactly the same way in both the primary and secondary samples in order to apply the Björklund and Jäntti two-sample estimator. For education, there are seven categories in the SFIE but twenty categories in the TSCS. We aggregate the finer categories in the TSCS to the seven categories in the SFIE: no formal education, elementary school, middle school, general high school, vocational high school, junior/vocational college, university and above.[10] The TSCS records industries using Taiwan's standard 2-digit industrial classification system, but the SFIE only records the 1-digit categories. We use the 1-digit categories that are identical in both datasets: agriculture, fishing, and forestry; mining; manufacturing; utilities; construction; wholesale and retail trade; transport, storage, and communication; finance, insurance, real estate, and business services; education, public administration, and personal services. The TSCS reports occupations using its own 3-digit classification. We aggregate the occupations in the TSCS to the seven 1-digit occupational categories in the SFIE: professionals and technicians; administrative executives and managerial workers; clerical workers; sales workers; service workers; agricultural, fishery, and forestry workers; production workers, transport workers, and laborers.[11]

Table 1 presents the ages, earnings, and distributions of education levels, industries, and occupations of fathers and sons. We apply corresponding sampling weights in each dataset to create descriptive statistics. Columns (1) and (2) show the distributions of earnings predictors of sons and their fathers from the 2005–2010 TSCS. Although sons' earnings predictors are not needed for estimation, they vividly illustrate the generational changes in the Taiwanese labor force. For example, the sons are far more educated and less likely to work in the agricultural sector. Column (3) reports earnings, age, and the distributions of earnings predictors for working males aged 40–55 from the 1978–1981 SFIE. Columns (2) and (3) show that the two samples are indeed comparable and match each other well in terms of the relative distributions of earnings predictors. Still, minor differences exist. For example, compared to the

[10] We combine illiterate and no formal education into one category. We treat both 2-year and 4-year military and police academies as vocational colleges. Cadet school is coded as vocational high school.
[11] All the agriculture, fishing, and forestry workers are in the agriculture, fishing, and forestry industry. However, that industry also includes managerial workers such as farm owners.

working males in the SFIE, there is a higher proportion of real fathers in the TSCS who have no formal education, who work in the agriculture, fishing, and forestry industries, or who are agriculture, fishing, or forestry workers. Some of the difference may be due to reporting error, since the TSCS asks survey participants to recall information about their fathers from decades earlier. It is also possible that real fathers are from slightly older cohorts than the working males in the SFIE.

4.2. The Earlier Period, 1990–1994

For the earlier period, we use the TSCS from 1990, 1991, 1992, and 1994 to create our primary sample of sons.[12] The TSCS in those years asked respondents what their father's education level, industry, and occupation was when they were 15 years old (1992 and 1994) or 18 years old (1990 and 1991), if their fathers were alive at that time. The coding of these earnings predictors is essentially the same as for the 2005–2010 TSCS, and we are able to aggregate to seven education categories, nine industry categories, and seven occupational categories.[13] Out of 2,758 males aged 35–50, 2,340 had fathers who were alive when they were 15 or 18 and have information available on their father's education level, industry, and occupation. We further restrict our primary sample to working males aged 35–50 (born from 1940–1959) with positive average monthly earnings. This leads to a sample size of 2,098 in our primary sample of sons.

In Table 2, column (1) presents age, earnings, and earnings predictors for the sons from the 1990–1994 TSCS data. The composition of the Taiwanese workforce in the early 1990s was very different from what it was in the late 2000s as shown in Table 1. For example, in column (1), while most people have some formal education, one-third of them have only an elementary school degree. (Taiwan increased its compulsory education requirement from six years to nine years in 1968.) Also, a substantial share of the labor force was still employed in the agricultural sector in the early 1990s. Column (2) shows the distributions of earnings predictors for the fathers reported in the 1990–1994 TSCS. It is clear that the fathers in Table 2 are older than the fathers in Table 1. The fathers in column (2) have very low educational attainments; less than

[12] We use one survey in 1990 and two surveys in 1991, 1992, and 1994. All data are from the second round of the TSCS.

[13] The top income bracket is TWD 200,000 in the 1990–1994 TSCS. Earnings in the 1990 TSCS are recorded in TWD 1,000 brackets. Earnings are recorded in TWD 20,000 brackets in the 1991 TSCS, while earnings in the 1992 and 1994 TSCS are recorded in TWD 10,000 brackets, as in the 2005–2010 TSCS. Only the 1992 and 1994 TSCS separate vocational high school from academic high school.

20% of them have a middle-school degree or higher. The agricultural sector accounts for a large share of Taiwan economy; half of the fathers in column (2) are agricultural, fishery, or forestry workers. It is easily seen from Tables 1 and 2 that since then Taiwan has significantly improved its workforce and been transformed from an agricultural to an industrial economy.

As the average age of sons in the 1990–1994 TSCS data was 41 years old, and they were asked for information about their fathers from when they were 15 or 18 years old, the secondary sample should be drawn from about 25 years earlier, i.e., the late 1960s. Unlike most newly developed countries, Taiwan has many extensive datasets from earlier years because of institutions that were first developed by the Japanese colonial government and later continued by the Taiwanese government. One limitation is that the original microdata of many early datasets are unavailable, so we can only rely on summary statistics from government publications. To investigate the validity of the father characteristics reported in the TSCS, we compare them with the summary statistics from the *1968 Statistical Abstract of Interior of the Republic of China*, which is available for every year since 1946 and which provides population counts by gender in each education, industry, and occupation category. Column (3) in Table 2 shows the distributions of education levels, industries, and occupations among employed males aged 15 and above in 1968.[14] The finance, insurance, real estate, and business services industry was not reported separately in 1968; rather, it was combined with the public administration, education, and personal services industry. Even though we cannot restrict the age range in column (3), the distributions of industry and occupation in column (3) are fairly similar to those in column (2). Unfortunately, the *1968 Statistical Abstract of Interior of the Republic of China* does not report earnings.

The SFIE was first conducted biennially from 1964–1970 with a sample size of about 3,000 households, but its microdata from before 1976 are not available. Fortunately, the *1968 Report on the Survey of Family Income and Expenditure* provides information on average household earnings by occupation of household heads. For robustness, we also use average earnings from the 1970 SFIE report.[15] In Table 3, the

[14] The levels of education are from the *Taiwan Demographic Fact Book, Republic of China* because the *Statistical Abstract of Interior of the Republic of China* does not separate a university degree from a junior college degree. The data in both reports are from the same source. The distribution of education in column (3) is based on all males aged 15 and above who are not students, regardless of their employment status.

[15] The 1970 data are from the *1974 Report on the Survey of Personal Income Distribution in Taiwan Area*, which includes information back through 1970. The *Report on the Survey of Family Income and*

upper and middle panels present the distributions, average household monthly earnings, and the average numbers of people employed per household in 1968 and 1970 by occupation of household heads. The distributions of household heads' occupations in 1968 and 1970 are quite close to the real fathers' occupations in Table 2. So the SFIE data are indeed drawn from a population comparable to the real fathers in the TSCS. The lower panel shows the same information in 1981 from the 1981 SFIE government report. The distribution of occupations in 1981 is also similar to fathers' occupations in Table 1.

5. Methodology

5.1. Theoretical Model

The theoretical properties of intergenerational elasticity have been thoroughly discussed in Solon (1992), Björklund and Jäntti (1997), and many other papers. In this section, we briefly discuss sources of bias in the Björklund and Jäntti two-sample estimator and explain how we have addressed them.

If the data provide lifetime earnings for both generations, we can easily estimate the intergenerational earnings elasticity by OLS:

1) $$y_i^s = \alpha + \beta y_i^f + e_i,$$

where y_i^s and y_i^f are the permanent earnings of sons and their fathers in logarithm, and e_i is an error term that is orthogonal to y_i^f. The intergenerational earnings elasticity, β, is the linear projection of y_i^s on y_i^f and it is therefore not a causal relationship but a correlation. One can show that β is the correlation coefficient between y_i^s and y_i^f when their variances are equal to one other. In practice, researchers often rely on short-run measures such as current earnings as a proxy for permanent earnings, but this introduces a measurement error into the variables and causes the estimate of β to be biased. Generally either a noisy independent variable or a noisy dependent variable could cause bias in the estimate. Haider and Solon (2006) point out that the traditional classical measurement error assumption is not valid in this context because of changing earnings

Expenditure series does not include the SFIE data from Taipei city (the capital) after 1968 due to the separation of responsible statistics departments. The 1981 data are from the *1981 Report on the Survey of Personal Income Distribution in Taiwan Area*.

profiles over the life cycle.[16] In this paper, we follow Haider and Solon (2006) and restrict our primary samples to males aged 35–50 to minimize the life-cycle bias.

Let $y_i^f = X_i^f \Upsilon + v_i$, where X_i^f is a vector of predictors of permanent earnings and v_i is an error term that is orthogonal to X_i^f. Now suppose that fathers' earnings y_i^f are not available, and only X_i^f is observed in the primary dataset. If there exists a secondary sample that is from the same underlying population as the actual fathers and with information on both earnings and their predictors, we can estimate $\widehat{\Upsilon}$ in the secondary sample and then obtain the imputed values $\hat{y}_i^f = X_i^f \widehat{\Upsilon}$ in the primary sample.

Replace y_i^f by $\hat{y}_i^f$ in Equation (1):

2) $y_i^s = \alpha + \beta \hat{y}_i^f + e_i^*,\ e_i^* = \beta(y_i^f - \hat{y}_i^f) + e_i = \beta v_i + e_i.$

Kim (2017) provides a proof for consistency of the above two-sample estimator in equation (2) proposed by Björklund and Jäntti (1997) based on the following two assumptions: $\mathrm{Cov}(X_i^f, e_i) = 0$ and $\hat{y}_i^f$ is a consistent estimate of $X_i^f \Upsilon$. These two assumptions do not always hold, however. Solon (1992) points out one potential problem of using imputed values. While y_i^f and e_i are orthogonal by construction, $\hat{y}_i^f$ may not be orthogonal to e_i^* because X_i^f could be correlated with e_i. Using imputed earnings likely introduces upward bias into the estimate of β when intergenerational transmissions of worker characteristics are stronger than the intergenerational transmission of earnings. For example, a father's and a son's genetic cognitive abilities are probably strongly correlated, even conditional on the father's permanent earnings. The estimates based on earnings imputed by educational attainment are likely upward biased because they capture not only intergenerational earnings transmission but intergenerational transmission of cognitive abilities. We address this problem by using different sets of earnings predictors to test the robustness of our results.

Imputation bias occurs when $\hat{y}_i^f$ is not a consistent estimate of $X_i^f \Upsilon$. $\widehat{\Upsilon}$ represents the relationship between earnings and their predictors in the secondary sample.

[16] The life-cycle bias arises because the slope coefficient in the linear projection of current (observed) earnings on permanent earnings differs from unity at the early or late stage of the life cycle. ($y^{permanent} = \lambda y^{short\text{-}run} + \varepsilon$, where $\lambda \neq 1$.) In fact, life-cycle bias could result in amplification bias rather than attenuation bias.

Therefore, if the secondary sample does not represent the population of actual fathers and the labor market in which these fathers were working at their prime working age, $\widehat{\Upsilon}$ is unlikely a consistent estimate of Υ. The representativeness of the secondary sample is particularly a concern in a fast-growing economy, where returns to education or to different occupations can change substantially in a short period of time. Moreover, imputed earnings could suffer the same life-cycle bias as actual earnings, due to life cycles in some earnings predictors. For example, people change occupations more often at the start and perhaps the end of their careers. A father's current occupation (when his son is at his prime working age) may not be the same as his own prime-age occupation, and so it is not a good predictor for permanent earnings. Similar to actual earnings, the earnings predictors X_i^f need to be drawn from the time when the fathers were at their prime working age. In this paper, to minimize imputation bias, we carefully chose both the earnings predictors and the secondary sample to be consistent with the time when the fathers were at their prime working age.

5.2. Empirical Regression

In this section, we discuss the regressions for the Björklund and Jäntti two-sample method in the more recent period and then the regressions for the proxy method in the earlier period.

To estimate intergenerational earnings elasticity in 2005–2010, we first estimate the following model by OLS using the SFIE sample, in order to predict fathers' missing earnings:

3) $$y_i^f = X_i\Upsilon + age_i + age_i^2 + \textit{ SFIE year dummies} + \varepsilon_i,$$

where y_i is average monthly earnings in logarithm and X_i is a vector of earnings predictors including dummy variables for the seven education levels, nine industry categories, and seven occupational categories. We also control for age and its square and dummy variables for each year in the SFIE.

Next, we use $\widehat{\Upsilon}$ to predict the permanent component of fathers' log earnings, and we then regress sons' log earnings on fathers' predicted log earnings in the TSCS sample:

4) $y_i^s = \beta\hat{y}_i^f + age_i^s + age_i^{s2} + TSCS\ year\ dummies + u_i$,

where y_i^s is sons' log average monthly earnings and $\hat{y}_i^f = X_i^f\hat{\Upsilon}$ is fathers' predicted log average monthly earnings based on a vector of earnings predictors X_i^f reported in the TSCS. We control for sons' age, age squared, and dummy variables for each year in the TSCS. The coefficient of interest is β, intergenerational earnings elasticity. In order to account for randomness in the two different samples, we resample both the primary and secondary samples with 1,000 replications to obtain the bootstrapped standard errors as suggested by Björklund and Jäntti (1997) and Inoue and Solon (2010).[17] Since introducing sampling weights complicates the bootstrap, we adopt a practice that is common in the literature and we do not use sampling weights in all of the regressions. All of the point estimates in this paper are quantitatively similar with sampling weights.

To estimate intergenerational earnings elasticity from 1990–1994, we replace fathers' missing earnings by average occupational earnings and estimate the following model by OLS:

5) $y_i^s = \beta\bar{y}_i^o + age_i^s + age_i^{s2} + TSCS\ year\ dummies + u_i$,

where y_i^s is sons' log monthly earnings and $\bar{y}_i^o$ is average earnings by occupation in logarithm. $\bar{y}_i^o$ is obtained by dividing average household earnings (column (2) in Table 3) by the average number of people employed (column (3) in Table 3) and then taking the logarithm. Because our focus is to investigate the change in intergenerational earnings mobility, we also estimate Equation (5) using the 2005–2010 TSCS data, where average occupational earnings are calculated from the 1981 SFIE report. We use bootstrap to estimate the standard errors with 1,000 replications.[18]

Notice that predicted earnings without an age adjustment are simply the average earnings by occupation, when occupations are the only earnings predictors in Equation

[17] Inoue and Solon (2010) provide a consistent estimator for the standard error. We use the Stata codes provided by Pacini and Windmeijer (2016) that also account for heteroskedasticity and find that the standard errors are quantitatively similar to bootstrap standard errors reported in the paper. These results are available upon request.
[18] The estimated standard errors could be underestimated in the proxy method because we do not have a secondary sample and therefore ignore randomness in the average earnings. However, in Table 8, the estimated (bootstrap) standard errors using averages (columns (5) and (6)) are similar to those using microdata (columns (7) and (8)). Therefore, the magnitude of bias should be small.

(3). If we have average earnings of household heads, Equation (5) is essentially the same as applying the Björklund and Jäntti two-sample method in a secondary sample of household heads without restricting their age and gender. As most real fathers are household heads, this proxy method should introduce little bias into the estimates, even with an unrestricted secondary sample. However, since only household earnings are available in the SFIE government reports, the average earnings that we construct, $\bar{y}_i^o$, suffer a division bias and contain a measurement error. $\bar{y}_i^o$ assumes an equal share of earnings among workers within a household and therefore underestimates the average earnings of household heads. If the magnitudes of measurement error, the ratios of $\bar{y}_i^o$ to true household head earnings, differ across occupations, the estimate of β in Equation (5) would be biased. More importantly, while the estimates may be biased, we can still compare the estimated elasticities from the two periods, so long as the magnitudes of bias remain stable, that is, if these ratios do not change over time in each occupational category. [19] [20]

As robustness checks, in the above log-log regressions we relax the assumption that fathers' and sons' log earnings follow a bivariate lognormal distribution and we estimate Equations (4) and (5) using interval regressions and Poisson regressions. Moreover, we estimate rank-rank regressions that are more robust to nonlinearity between fathers' and sons' log earnings, measurement error, and life-cycle bias (Nybom and Stuhler 2017; Chetty, Hendren, Kline, Saez, et al. 2014). In the current context, because y_i^s, $\hat{y}_i^f$, and $\bar{y}_i^o$ are measured in percentile ranks, measurement error in y_i^s, $\hat{y}_i^f$, and $\bar{y}_i^o$ should cause little bias in the rank-rank regression, and we also need to be less concerned about imputation bias and intergenerational transmission of worker characteristics, which could otherwise introduce upward bias in the estimates for intergenerational elasticity. Nevertheless, in the current context, one disadvantage is that variation in fathers' percentile ranks is constrained by imputed earnings, which could instead introduce downward bias to estimates for the rank-rank slope.

[19] We calculate these ratios using the 1981 SFIE microdata and find that they are fairly similar across occupations. These ratios range from 0.7–0.8, except for the category of agricultural workers, in which the ratio is 0.6. If these ratios are similar in the 1968 and 1970 SFIE data, the bias in our estimates due to measurement error in $\bar{y}_i^o$ is probably not large.

[20] We find that the average share of household wages earned by household heads is about 80% in both 1966 and 1981. Unfortunately, this information is only available for wage income, and we are not able to compare it within occupations because the occupational categories in the 1966 report are not comparable to those in later reports.

6. Estimation Results

6.1. Intergenerational Mobility in Taiwan and Change Over Time

In Table 4, we present estimates for the earnings predictors from Equation (3) in the SFIE sample. The omitted education category is no formal education, and agriculture, fishing, and forestry are the omitted industry and occupational categories. All of the estimates for levels of education and occupations are positive and significant, but the estimates for industries are not significant, probably due to collinearity between industries and occupations. The estimates are generally consistent with our expectations. For example, workers with better education earn more, managerial workers have the highest earnings, and so forth. The more important statistic in Table 4 is the R-squared that measures the predictive power of the regressors. The adjusted R-squared equals 0.45. Because our goal is to predict permanent earnings, we calculate the partial R-squared from the above regression by partialling out age, age squared, and dummies for each year. The partial R-squared remains a good size and equals 0.37, indicating that level of education, industry, and occupation are strong predictors of the permanent component of earnings.

We report the Björklund and Jäntti two-sample estimates of intergenerational earnings elasticity from Equation (4) in Table 5. In column (1), we use all the earnings predictors shown in Table 4 and regress sons' log monthly earnings on their fathers' imputed log monthly earnings. The estimate of intergenerational earnings elasticity is 0.47. Our estimate is substantially greater than the previous estimates of 0.18 from Kan, Li, and Wang (2015) and 0.25 from Sun and Ueda (2015). One reason for the substantially greater estimate is that we correct the imputation bias in both studies by using retrospective information on father's earnings predictors and a carefully chosen secondary sample. Another reason is that we use a representative primary sample instead of a co-residing sample. As Solon (1992) has pointed out, non-representative samples can cause severe downward bias in the estimates. In fact, if we restrict our primary sample to working males aged 26–45 years old who are co-residing with their fathers, as in Kan, Li, and Wang (2015), we find a similar intergenerational earnings elasticity of 0.20 (not reported in the paper). Our result shows that intergenerational earnings mobility in Taiwan is not as high as previous studies suggest.

In columns (2) – (4), instead of using all earnings predictors, we use only two out of three sets of predictors to impute fathers' earnings. The estimates remain quantitatively similar to column (1), ranging from 0.41–0.49. In the last three columns, columns (5) – (7), only one set of earnings predictors is used to impute fathers' earnings. Using only industry or occupation yields similar estimates of 0.40–0.42. However, using only level of education gives a much larger estimate of 0.65. As education is strongly correlated with earnings-generating traits and abilities, and intergenerational transmission of these traits is likely stronger than intergenerational earnings transmission, using earnings imputed by education may introduce upward bias into the estimates (Solon 1992). Given the intense competition in the Taiwanese education system, such a mechanism is probably even stronger in Taiwan, and it is not surprising to get a large (but biased) estimate for intergenerational earnings elasticity when education attainment is used as the sole predictor.

Many recent studies raise concerns about the canonical log-log linear model. The estimates could be quite unstable when the assumption of linearity between parental and child log earnings does not hold and they therefore do not follow a bivariate lognormal distribution (Jerrim, Choi, and Simancas 2016; Mitnik et al. 2015; Chetty, Hendren, Kline, and Saez 2014; Nybom and Stuhler 2017).[21] In Table 6, we repeat Table 5 but estimate intergenerational earnings mobility using different functional forms. In the upper panel, because earnings in the TSCS are reported in intervals (see Note 6), we estimate intergenerational earnings elasticity using interval regressions. Mitnik et al. (2015) point out that the slope coefficient in a log-log linear model generally measures the *elasticity of the conditional geometric mean*, which does not have a natural economic interpretation.[22] In the middle panel, we follow their recommendation to use Poisson regressions to estimate intergenerational earnings elasticity.[23] All of the estimates in the upper and middle panels of Table 6 are nearly identical to those in Table 5.

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[21] To address the linearity assumption, in addition to the robustness checks in Table 6, we impute fathers' earnings in levels instead of in logarithms and then regress sons' log earnings on fathers' log imputed earnings. The results remain quantitatively similar to those in Table 5 and are available upon request. Note that the estimates for age and year dummies in Equation (4) are needed for predicting fathers' earnings in levels.

[22] $E[\ln(y)|x] = \alpha + \beta\ln(x)$ implies $\ln[\exp[E(\ln(y)|x)]] \equiv \ln[GM(y|x)] = \alpha + \beta\ln(x)$, where GM denotes the geometric mean operator.

[23] We estimate the following conditional mean by the Poisson pseudo maximum likelihood: $E(y_i^s|\cdot) = \exp(\beta\hat{y}_i^f + age_i^s + age_i^{s2} + \textit{TSCS year dummies})$, where y_i^s is son i's earnings in levels and $\hat{y}_i^f$ is his father's imputed log earnings. (We continue to restrict sons' earnings to be nonzero.) In the Poisson model, $\beta = \frac{\partial\ln[E(y_i^s|\cdot)]}{\partial\ln(\hat{y}_i^f)}$ measures the elasticity of conditional mean of sons' earnings with respect to fathers' earnings.

In the lower panel, we measure (imputed) earnings in percentile ranks and estimate rank-rank regressions as in Chetty, Hendren, Kline, and Saez (2014).[24] The slope coefficient of a rank-rank regression is the correlation coefficient between a child's position in the earnings distribution and his parents' position in the distribution, and it measures relative mobility across generations, which is similar to intergenerational earnings elasticity. In the lower panel, columns (1) – (4), the estimates for rank-rank slope are around 0.28 when two or three sets of earnings predictors are used.[25] Like intergenerational earnings elasticity, the rank-rank slope in Taiwan is similar in magnitude to that in the U.S. (Chetty, Hendren, Kline, and Saez 2014; Mazumder 2016), suggesting relatively low intergenerational mobility in Taiwan. In columns (5) – (7), when only one set of earnings predictors is used, the estimates vary a bit, ranging from 0.19–0.30. The estimates are still fairly close to the estimate in column (1). Note that the estimate in column (7), which is based on education, is not strongly biased upward like those in the upper two panels. The rank-rank slope is more robust to the bias due to intergenerational transmission of worker characteristics. To check the robustness further, we use working males aged 40–55 from the Manpower Utilization Survey (MUS) in 1978–1982 as another secondary sample. The results are reported in Appendix Table A2 and are quantitatively similar to those in Table 5 and 6.[26]

Table 7 presents the estimates of intergenerational earnings elasticity from log-linear regressions by age group (in the upper panel) and by cohort (in the lower panel). All three earnings predictors are used to predict fathers' earnings: level of education, industry, and occupation. In the upper panel, in column (1) we increase the age range of sons in the TSCS data to 30–55 years old. (The age range in the SFIE sample remains 40–55 years old.) The estimate for intergenerational earnings elasticity is 0.47, nearly identical to the estimate in column (1) of Table 5. Columns (2) – (5) show the estimates

[24] We first partial out ages (and their squares) and year dummies from sons' earnings and rank the residuals. We then estimate: $y_i^s = \beta \hat{y}_i^f + age_i^s + age_i^{s2} + TSCS\ year\ dummies + u_i$, where y_i^s is the percentile rank of son i's residual earnings and $\hat{y}_i^f$ is the percentile rank of his father's imputed log earnings.

[25] One advantage of the rank-rank regression is to include zero earnings. The estimate for rank-rank slope that includes zero earnings is 0.26 (nor reported).

[26] The earnings information available in the MUS is a bit different from the earnings information in the SFIE and TSCS. The MUS reports regular monthly earnings from the primary job, while SFIE and TSCS report annual/average monthly earnings from all jobs. 98% of working males aged 40–55 report having only one job. However, it is very common in Taiwan for employees to receive a substantial bonus at the end of the year. The reported earnings in the MUS sample are 25% lower than in the SFIE sample.

in four overlapping age groups: 30–40, 35–45, 40–50, and 45–55. There appears to be life-cycle bias in the youngest age group. In column (2), the estimate for 30–40 year olds is only 0.33, smaller than the estimates for the older age groups. In columns (3) and (4), the two age groups belong to the main sample (ages 35–50), and the results are quantitatively similar to the results in Table 5. The estimate in column (5) is a bit large. Because the real fathers in column (5) would be older, the earnings relationships estimated from the 1978–1982 SFIE sample may be less reflective of the earnings structure for some of these fathers. We restrict our main sample in Table 5 to a narrow age range because of the potential threats of imputation bias and life-cycle bias.

Many studies in the literature, such as Lefranc, Ojima, and Yoshida (2014), Kan, Li, and Wang (2015), and Fan, Yi, and Zhang (2015), rely on cohort-specific estimates to identify the change in intergenerational mobility. However, this approach is problematic because of collinearity between age and cohort (Lee and Solon 2009). In Table 6, the lower panel vividly illustrates this problem. The estimates from the five overlapping cohorts show exactly the same pattern as the age-specific estimates in the upper panel. The estimates are smaller among the younger cohorts and larger among the older cohorts. The differences in the estimates across cohorts likely reflect life-cycle bias rather than changes in intergenerational earnings mobility. Therefore, we need additional data from an earlier period in order to estimate intergenerational mobility for older cohorts. One might be concerned that our main sample (columns (3) and (4) in the upper panel) also contains a small fraction of cohorts that could be too young or too old. For example, fathers' earnings for people born in 1955 are predicted using the 1978–1982 SFIE sample, but the information on father's earnings predictors was actually drawn from 1970, when these people were 15 years old. To address this concern, note that the cohort in column (3) in the lower panel is strictly consistent with the sample period of the SFIE sample, and that the estimate is nearly identical to the main results in Table 5.

In Table 8, we investigate the change in intergenerational earnings mobility using data from an earlier period. In columns (1) – (4), the primary sample for sons is the 1990–1994 TSCS. In columns (5) – (8), the primary sample for sons is the 2005–2010 TSCS. The two samples come largely from different cohorts; the sons in the 2005–2010 TSCS were born from 1955–1975, while the sons in the 1990–1994 TSCS were born from 1940–1959. In columns (1) and (2), average earnings are based on seven occupational categories, and the estimate for intergenerational earnings elasticity is

0.38. In the SFIE government reports, average earnings for 1968 are originally reported in nine categories and average earnings for 1970 in eight categories.[27] Columns (3) and (4) show the results based on these slightly finer averages. The estimates are nearly identical, equal to 0.38. In columns (5) and (6), we proxy fathers' permanent earnings by average earnings in seven or nine occupational categories from the 1981 SFIE report. The estimates for intergenerational earnings elasticity are 0.36–0.37. The results suggest that intergenerational earnings elasticity has remained stable in Taiwan from the early 1990s to the late 2000s.

As discussed previously, using average earnings by occupation as a proxy for fathers' permanent earnings is similar to using earnings predicted by occupation. Indeed, the estimates in columns (5) and (6) are comparable to the two-sample estimate in column (6) of Table 5. In columns (7) and (8), we estimate intergenerational earnings elasticity by the Björklund and Jäntti two-sample approach, where fathers' permanent earnings are predicted by seven occupational categories from the 1981 SFIE microdata. Since the main source of bias in the previous columns is measurement error in $\bar{y}_i^o$ – that is, dividing average household earnings by the average number of people employed per household – we utilize the microdata in column (7) and take economic household heads as the secondary sample to correct the measurement error, but we leave the age and gender of these household heads unrestricted. In column (8), we further restrict household heads to males aged 40–55. The two-sample estimates for intergenerational earnings elasticity equal 0.40–0.41, which are similar in magnitude to the estimates in columns (5) and (6), which use average earnings as a proxy. Therefore, the measurement error in $\bar{y}_i^o$ does not seem to cause large bias in our data.

In Table 9, we repeat Table 8 and compare intergenerational earnings mobility between the early 1990s and the late 2000s using interval regressions, Poisson regressions, and rank-rank regressions. In the upper and middle panels, the estimates for intergenerational earnings elasticity are roughly around 0.40, which is quantitatively similar to the estimates in Table 8. In the lower panel, the estimates for rank-rank slope are 0.31–0.32 in 1990–1994 and 0.25–0.27 in 2005–2010. This continues to suggest that there was no substantial change in intergenerational earnings mobility in Taiwan

[27] In the 1968 SFIE report, transport workers and mining workers are separate from production workers and laborers. In the 1970 SFIE report, transport workers are reported as an individual category. In the 1981 SFIE report, transport workers, production workers, and laborers are reported as three individual categories.

between those periods. Because the estimates in the lower panel essentially capture intergenerational rank association in *occupation*, these estimates need to be interpreted with some caution as to what extent such correlation represents intergenerational rank association in *earnings*. Nevertheless, given that the estimate based on occupational rank is quantitatively similar to the estimate based on all predictors in Table 6, these estimates are likely a good indication of the intergenerational rank correlation in earnings. Notice that the measurement error in $\bar{y}_i^o$ from the proxy method is no longer a problem in rank-rank regressions. The estimates in columns (7) and (8) become the same as the estimate in columns (5) because the rank of predicted occupational earnings is the same as the rank of average occupational earnings. Overall, Table 9 shows that the finding of stable intergenerational earnings mobility in Table 8 is robust to different model specifications and to an alternative measure of mobility.

6.2. Regional Difference in Intergenerational Mobility

While intergenerational earnings elasticity must be estimated using the entire earnings distribution from a representative sample because elasticity is measured relative to the population mean, rank-rank slope can be estimated for subpopulations (Chetty, Hendren, Kline, and Saez 2014; Bhattacharya and Mazumder 2011). For example, Chetty, Hendren, Kline, and Saez (2014) find that there is substantial geographical variation in income-rank association in the U.S. and that intergenerational mobility is higher in places with better schools, less segregation, and less income inequality. Since urbanization is an important part of the economic development process and our sample sizes for small geographical areas are not large enough, we focus on the difference in intergenerational mobility between metropolitan and nonmetropolitan areas. Note that the percentile ranks of fathers and sons in each area are still based on national ranks as in Chetty, Hendren, Kline, and Saez (2014).

The TSCS data provide zip codes for survey participants' birthplaces and current residences.[28] We aggregate the zip codes to 21 counties and cities and define major cities to be metropolitan areas.[29] In Table 10, we estimate the rank-rank slope in

[28] The TSCS also has information on where respondents were living before age 15, but the information is only available for 2005, 2007, and 2010. Although a person's birthplace is not necessarily where they grew up and where their father was working, only 7% of the sons report a different metropolitan status for their birthplaces than for their residences before age 15.

[29] We use the pre-1982 administrative divisions that include two special municipalities, 3 provincial cities, and 16 counties in Taiwan. The geographical boundaries of these administrative divisions were mostly the same from 1949 to 2010. We define the two special municipalities (Taipei city and Kaohsiung city),

2005–2010 by metropolitan status of birthplace and current residence. In all columns, fathers' earnings are imputed by education, industry, and occupation.[30] First, there is substantial migration to metropolitan areas: more than one third of sons in the primary sample who are living in metropolitan areas were born outside these areas, while almost no people from metropolitan areas have moved to nonmetropolitan areas. Second, intergenerational earnings mobility in metropolitan areas appears to be higher than in nonmetropolitan areas in 2005–2010, especially for native residents who were born and continue to live in the metropolitan areas. The rank-rank slope estimate in column (1) is 0.13 and statistically significantly lower than the estimate of 0.30 in column (3). Not only do metropolitan areas in Taiwan have better schools and job prospects, they also have lower cross-sectional inequality in income and educational attainment (Wu 2011). So the higher intergenerational mobility in metropolitan areas is consistent with the finding in Chetty, Hendren, Kline, and Saez (2014). The estimate in column (2) is statistically significantly lower than the estimate in column (3). So people who migrate to metropolitan areas from nonmetropolitan areas have higher intergenerational mobility than non-migrants, that is, people who were born and continue to live in nonmetropolitan areas. In Appendix Table A3, we estimate the rank-rank slope by metropolitan status in 1990–1994 and 2005–2010. There was little change in intergenerational earnings mobility between the two periods, except for people who were born and continued to live in metropolitan areas, whose intergenerational mobility appears to have been lower in the earlier period.[31]

7. Discussion and conclusion

In this paper, we estimate intergenerational earnings mobility in Taiwan in 1990–1994 and 2005–2010. We use representative primary and secondary samples and correct problems common in the literature such as life-cycle bias and imputation bias.

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3 provincial cities (Keelung city, Taichung city, and Tainan city), and one county (Taipei county) to be metropolitan areas. Taipei county surrounds both Taipei city (the capital) and Keelung city, and it is part of the Taipei-Keelung metropolitan area. In 2010, these 3 provincial cities were combined with their counties and upgraded to special municipalities. Taipei county itself became a special municipality in 2010.

[30] The estimates in Table 10 are nearly identical if we also use birth locations to impute earnings. The sample size deceases to 1,287 because some people were not born in Taiwan.

[31] As many native residents in metropolitan areas in 2005–2010 are second-generation migrants from nonmetropolitan areas, migration and urbanization likely contribute to the improvement in intergenerational mobility. Indeed, while income inequality increased in Taiwan from 1990 to 2010, it generally increased at slower rates in metropolitan areas than in nonmetropolitan areas (Wu 2011).

We do not rely on co-residing father-son pairs and restrict a narrow age range in our primary sample to reflect that Taiwanese men enter the labor market relatively late and retire relatively early. Our secondary samples for potential fathers are carefully chosen so that they are indeed representative of real fathers in the primary sample. We estimate the log-log regressions as well as interval regressions, Poisson regressions, and rank-rank regressions, which relax the assumption of linearity between parent and child log earnings. We find robust estimates that in Taiwan intergenerational earnings elasticity is 0.4–0.5 and intergenerational rank association in earnings is 0.3.

The finding that intergenerational earnings mobility in Taiwan is similar to that in relatively less mobile countries such as the U.S. is especially notable. As Taiwan and other Asian Tigers share many similarities, we suspect that the high mobility estimated for them is a result of estimation bias, and that true intergenerational mobility in the Asian Tigers is much lower than the previous literature suggests. Surprisingly, intergenerational earnings mobility in Taiwan appears to have remained relatively stable, despite dramatic economic and social changes during the period studied. One explanation is that different causal channels cancel each other out. For example, an increase in returns to education may reduce intergenerational earnings mobility, while an increase in public investment in education will raise intergenerational earnings mobility (Solon 2004). Indeed, during the period from 1990–1994 to 2005–2010, the returns to an additional year of education in Taiwan increased from 7.8% to 11.0%, while the intergenerational elasticity of years of education decreased from 0.35 to 0.21.[32] (The compulsory education requirement increased from six years to nine years in 1968.) Moreover, research has shown substantial intergenerational transmission of personality characteristics, including both cognitive and non-cognitive abilities (Rustichini, Iacono, and McGue 2017; Blanden, Gregg, and Macmillan 2007; Grönqvist, Öckert, and Vlachos 2016). Therefore, intergenerational earnings mobility could have been relatively stable because intergenerational transmission of abilities is stable and plays a substantial role.[33]

[32] The intergenerational elasticity of years of education is estimated by the authors from the TSCS data and available upon request.

[33] Lefgren, Lindquist, and Sims (2012) and Cardak, Johnston, and Martin (2013) suggest that intergenerational ability transmission accounts for the majority of intergenerational income mobility in Sweden and the U.S. Since the estimate based on earnings imputed by education attainment is very large (column (7) of Table 5), intergenerational ability transmission is likely strong in Taiwan and probably plays a major role in intergenerational earnings mobility. Unfortunately, our data are not rich enough for us to apply decomposition methods as in Lefgren, Lindquist, and Sims (2012) or Cardak, Johnston, and Martin (2013).

We note several aspects of this paper that future research could improve upon. First, since we do not have data on father's actual earnings and so rely on the Björklund and Jäntti two-sample approach, our estimates for them could be potentially biased upward by intergenerational transmission of worker characteristics, and they probably represent a upper bound of intergenerational earnings elasticity in Taiwan (Solon 1992). Second, due to the sample sizes, we focus on intergenerational earnings mobility measured at the mean. It is possible that intergenerational mobility could have changed at the tails of income distribution, even though it is relatively stable at the mean. Indeed, some research shows that intergenerational mobility could be nonlinear, and lower at the tails of income distribution (Björklund and Jäntti 2009; Björklund, Roine, and Waldenström 2012). Moreover, similarly to most research in the literature, we estimate correlations but are unable to provide evidence on the causal mechanisms determining the persistence of income inequality. (See a comprehensive literature review by Black and Devereux (2011).) Finally, we only investigate intergenerational mobility across two generations. The persistence of economic status across three or more generations has attracted attention and been investigated in several developed countries (Braun and Stuhler 2016; Nybom and Stuhler 2014; Solon 2015; Olivetti, Paserman, and Salisbury 2016). Studying multi-generational mobility in a fast-changing economic environment could provide a better understanding of the role of economic development in intergenerational mobility.

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Table 1: Descriptive Statistics for the 2005–2010 TSCS and the 1978–1982 SFIE

	(1) 2005–10 TSCS Sons	(2) 2005–10 TSCS Fathers	(3) 1978–82 SFIE Fathers
Average Monthly Earnings	50833.7 (38668.8)		13824.5 (9416.4)
Age	42.7 (4.5)		46.0 (4.3)
Education (%)			
No Formal Education	0.0	18.6	10.0
Elementary School	4.1	54.2	53.0
Middle School	21.4	11.2	12.4
Vocational High School	36.0	4.5	7.2
Academic High School	6.0	4.8	7.1
Vocational College	17.7	3.5	4.4
University and above	14.8	3.2	5.8
Occupation (%)			
Professionals and Technicians	15.8	7.0	6.6
Administrative Executives and Managerial Workers	9.3	5.6	5.3
Clerical Workers	5.8	4.7	12.9
Sales Workers	13.0	13.0	12.3
Service Workers	10.0	7.2	6.8
Agricultural, Fishery, and Forestry Workers	4.4	33.3	26.9
Production Workers, Transport Workers, and Laborers	41.7	29.2	29.2
Industry (%)			
Agriculture, Fishing, and Forestry	4.8	34.8	27.0
Mining	0.5	1.7	1.6
Manufacturing	29.4	16.1	18.1
Utilities	0.7	0.9	1.3
Construction	13.7	9.4	8.6
Wholesale and Retail Trade	17.0	15.5	14.5
Transport, Storage, and Communication	6.8	6.6	8.7
Finance, Insurance, and Business Services	8.5	1.4	1.9
Education, Public Administration, and Personal Services	18.6	13.6	18.2
Observations	1,299	1,299	26,110

Note: Sampling weights are applied to all columns. Average monthly earnings are reported in nominal Taiwanese dollars. TSCS sons are 35- to 50-year-old working males, SFIE fathers are 40- to 55-year-old working-male household heads.

Table 2: Descriptive Statistics for the 1990–1994 TSCS

	(1) 1990 - 1994 TSCS Sons	(2) 1990 - 1994 TSCS Fathers	(3) 1968 TW Statistical Abstract
Average Monthly Earnings	37319.7 (27481.8)		
Age	41.1 (4.4)		
Education (%)			
No Formal Education	2.9	36.0	20.8
Elementary School	31.8	45.2	51.9
Middle School	19.6	7.6	12.2
Academic High School	15.7	5.1	5.4
Vocational High School	8.3	1.2	4.7
Vocational College	11.7	2.7	2.1
University and above	10.1	2.3	2.8
Occupation (%)			
Professionals and Technicians	10.5	4.0	3.8
Administrative Executives and Managerial Workers	9.6	5.1	2.0
Clerical Workers	9.0	7.5	6.0
Sales Workers	15.9	11.0	9.9
Service Workers	4.8	4.3	9.9
Agricultural, Fishery, and Forestry Workers	13.9	50.8	47.3
Production Workers, Transport Workers, and Laborers	36.2	17.3	21.0
Industry (%)			
Agriculture, Fishing, and Forestry	14.3	51.4	45.2
Mining	1.0	1.8	1.8
Manufacturing	28.1	10.8	11.7
Utilities	1.7	0.6	0.8
Construction	12.2	5.6	3.2
Wholesale and Retail Trade	14.6	11.3	9.6
Transport, Storage, and Communication	8.7	5.1	4.4
Finance, Insurance, and Business Services	3.7	1.0	n/a
Education, Public Administration, and Personal Services	15.8	12.5	23.3
Observations	2,098	2,098	n/a

Note: Sampling weights are applied to columns (1) and (2). Column (3) is taken from the 1968 Statistical Abstract. Average monthly earnings are reported in nominal Taiwanese dollars. In column (2), only the 1992 and 1994 TSCS separate vocational high school from academic high school. In column (3), the education distribution is based on the total male work force (aged 15 and above), while the industry and occupational distributions are based on the employed male work force. The two service industries were not separated in the 1968 Statistical Abstract.

Table 3: Descriptive Statistics for the 1968, 1970, and 1981 SFIE Government Reports

	(1) %	(2) Household Monthly Earnings	(3) # People Employed
Occupation 1968			
Professionals and Technicians	4.0	4,366	1.5
Administrative Executives and Managerial Workers	2.2	5,248	1.8
Clerical Workers	6.7	3,438	1.5
Sales Workers	12.9	3,233	1.9
Service Workers	4.6	2,411	1.6
Agricultural, Fishery, and Forestry Workers	47.4	2,326	3.1
Production Workers, Transport Workers, and Laborers	22.2	2,721	1.8
Occupation 1970			
Professionals and Technicians	4.0	4,211	1.5
Administrative Executives and Managerial Workers	3.9	5,476	1.6
Clerical Workers	7.7	4,092	1.6
Sales Workers	11.4	3,747	1.9
Service Workers	4.4	2,965	1.6
Agricultural, Fishery, and Forestry Workers	46.4	2,580	3.1
Production Workers, Transport Workers, and Laborers	22.2	3,242	1.9
Occupation 1981			
Professionals and Technicians	6.6	30,703	1.7
Administrative Executives and Managerial Workers	4.2	34,513	1.7
Clerical Workers	12.3	25,527	1.7
Sales Workers	13.0	21,980	1.9
Service Workers	5.8	19,336	1.8
Agricultural, Fishery, and Forestry Workers	25.8	15,702	2.7
Production Workers, Transport Workers, and Laborers	32.3	19,166	1.9

Note: Household average monthly earnings are annual earnings divided by 12 and are reported in nominal Taiwanese dollars.

Table 4: First Stage Regression from the 1978–1982 SFIE

Elementary School	0.126*** (0.010)	Professionals	0.745*** (0.074)	Mining	0.025 (0.076)
Middle School	0.239*** (0.013)	Managerial Workers	0.964*** (0.074)	Manufacturing	-0.034 (0.073)
Vocational High School	0.310*** (0.016)	Clerical Workers	0.592*** (0.073)	Utilities	0.082 (0.077)
Academic High School	0.315*** (0.016)	Sales Workers	0.595*** (0.075)	Construction	-0.081 (0.074)
Vocational College	0.364*** (0.019)	Service Workers	0.455*** (0.074)	Wholesale	0.035 (0.074)
University and above	0.502*** (0.018)	Production Worker	0.418*** (0.073)	Transport	0.120 (0.073)
				Business Services	0.123 (0.075)
				Personal Services	-0.084 (0.073)
Obs.			26,110		
Adj. R^2			0.45		
Partial Adj. R^2			0.37		

Note: The dependent variable is average monthly earnings in logarithm. Age, age squared, and dummy variables for the years 1979–1982 are controlled in the regression. OLS Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Estimates of Intergenerational Earnings Elasticity
in 2005–2010 from Different Predictors

	(1) All Predictors	(2) Industry & Occupation	(3) Education & Industry	(4) Education & Occupation	(5) Industry	(6) Occupation	(7) Education
IGE	0.466***	0.409***	0.487***	0.477***	0.396***	0.416***	0.648***
	(0.054)	(0.054)	(0.059)	(0.055)	(0.060)	(0.054)	(0.083)
Obs.	1,299	1,299	1,299	1,299	1,299	1,299	1,299

Note: The estimates are from log-linear regressions. Bootstrap standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Estimates of Intergenerational Earnings Elasticity and Rank-Rank Slope in 2005–2010

	(1) All Predictors	(2) Industry & Occupation	(3) Education & Industry	(4) Education & Occupation	(5) Industry	(6) Occupation	(7) Education
	Interval Regression						
IGE	0.461***	0.405***	0.477***	0.471***	0.384***	0.413***	0.640***
	(0.052)	(0.052)	(0.055)	(0.052)	(0.058)	(0.052)	(0.076)
	Poisson Regression						
IGE	0.470***	0.413***	0.466***	0.486***	0.352***	0.427***	0.627***
	(0.063)	(0.064)	(0.067)	(0.063)	(0.069)	(0.063)	(0.082)
	Rank-Rank Regression						
Rank	0.277***	0.239***	0.276***	0.282***	0.192***	0.250***	0.303***
	(0.030)	(0.029)	(0.030)	(0.030)	(0.029)	(0.030)	(0.033)
Obs.	1,299	1,299	1,299	1,299	1,299	1,299	1,299

Note: Bootstrap standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Estimates of Intergenerational Earnings Elasticity by Age Groups and Cohorts in 2005–2010

	(1)	(2)	(3)	(4)	(5)
Age Groups	Ages 30-55 (1950-1980)	Ages 30-40 (1965-1980)	Ages 35-45 (1960-1975)	Ages 40-50 (1955-1970)	Ages 45-55 (1950-1965)
IGE	0.471***	0.334***	0.437***	0.517***	0.580***
	(0.042)	(0.060)	(0.061)	(0.066)	(0.072)
Obs.	2,015	816	856	937	863
Cohorts	1970-80 (Ages 30-40)	1965-74 (Ages 31-45)	1960-69 (Ages 36-50)	1955-64 (Ages 41-55)	1950-59 (Ages 46-55)
IGE	0.332***	0.389***	0.484***	0.539***	0.568***
	(0.066)	(0.065)	(0.067)	(0.072)	(0.087)
Obs.	596	728	825	831	594

Note: The estimates are from log-linear regressions. Fathers' earnings are predicted by level of education, industry, and occupation. Bootstrap standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Estimates of Intergenerational Earnings Elasticity in 1990–1994 and 2005–2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1990–1994 TSCS				2005–2010 TSCS			
	1968 7. Occ.	1970 7. Occ.	1968 9. Occ.	1970 8. Occ.	1981 7. Occ.	1981 9. Occ.	1981 Microdata	1981 Microdata (restricted)
IGE	0.381***	0.378***	0.386***	0.384***	0.364***	0.365***	0.411***	0.404***
	(0.027)	(0.027)	(0.028)	(0.027)	(0.048)	(0.047)	(0.054)	(0.054)
Obs.	2,098	2,098	2,098	2,098	1,299	1,299	1,299	1,299

Note: The estiamtes are from log-linear regressions. Bootstrap standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 9: Estimates of Intergenerational Earnings Elasticity and Rank-Rank Slope in 1990–1994 and 2005–2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1990–1994 TSCS				2005–2010 TSCS			
	1968 7. Occ.	1970 7. Occ.	1968 9. Occ.	1970 8. Occ.	1981 7. Occ.	1981 9. Occ.	1981 Microdata	1981 Microdata (restricted)
	Interval Regression							
IGE	0.370***	0.367***	0.375***	0.373***	0.361***	0.362***	0.408***	0.401***
	(0.027)	(0.027)	(0.028)	(0.028)	(0.045)	(0.044)	(0.052)	(0.052)
	Poisson Regression							
IGE	0.361***	0.361***	0.365***	0.365***	0.373***	0.371***	0.425***	0.425***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.054)	(0.053)	(0.064)	(0.063)
	Rank-Rank Regression							
Rank	0.313***	0.313***	0.315***	0.315***	0.250***	0.269***	0.250***	0.250***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.029)	(0.029)	(0.030)	(0.030)
Obs.	2,098	2,098	2,098	2,098	1,299	1,299	1,299	1,299

Note: Bootstrap standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Estimates of Rank-Rank Slope in 2005-2010 by Metropolitan Status

	(1) Live/Born in Metropolitan	(2) Live/Not Born in Metropolitan	(3) Not Live/ Not Born in Metropolitan	(4) Not Live/ Born in Metropolitan
Rank	0.131** (0.062)	0.176** (0.073)	0.297*** (0.038)	0.218 (0.228)
Obs.	342	204	712	41

Note. The estimates are from rank-rank regressions. Bootstrap standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In all columns, fathers' earnings are imputed by level of education, industry, and occupation.

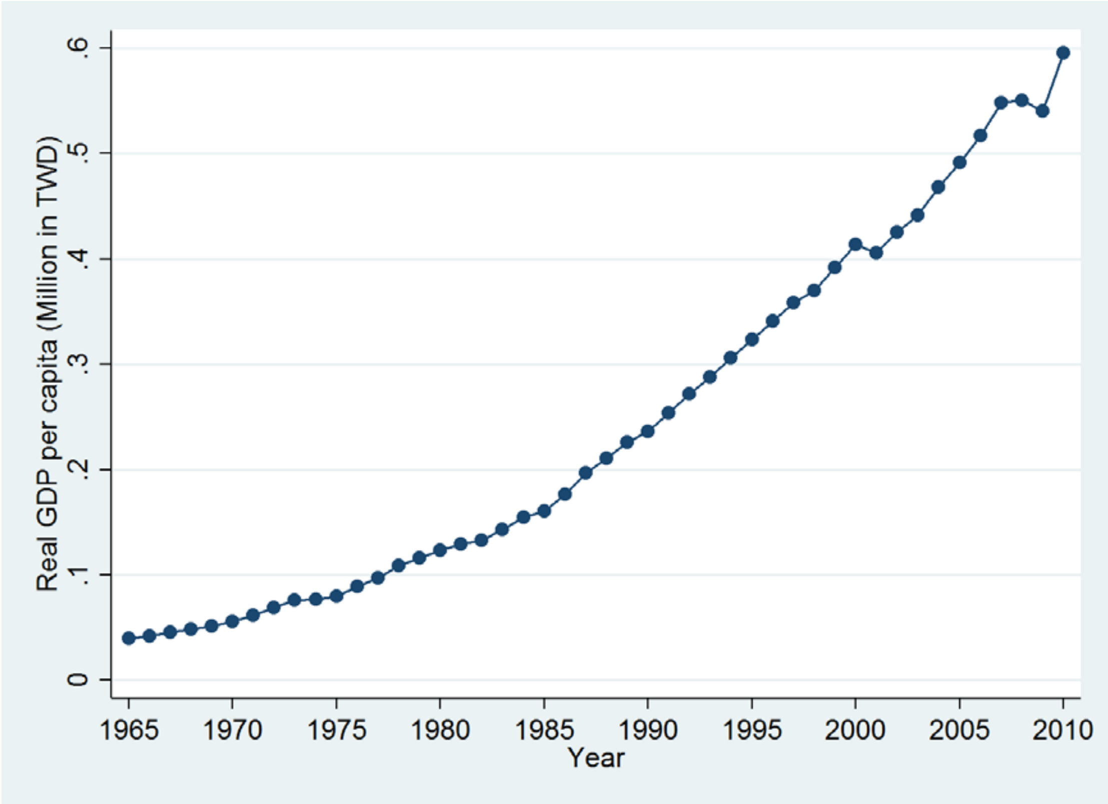

Figure 1: Real GDP per capita in Taiwan, 1965–2010 (2011 Taiwanese dollars).

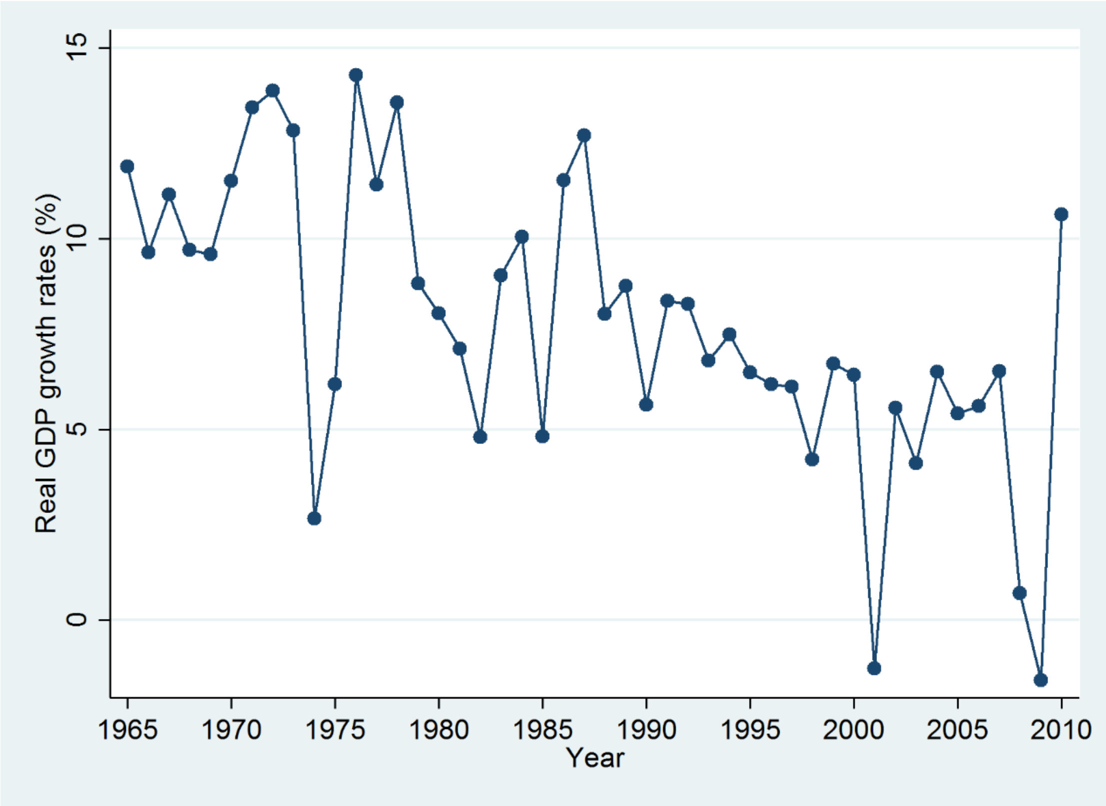

Figure 2: Real GDP Growth Rates in Taiwan, 1965–2010.

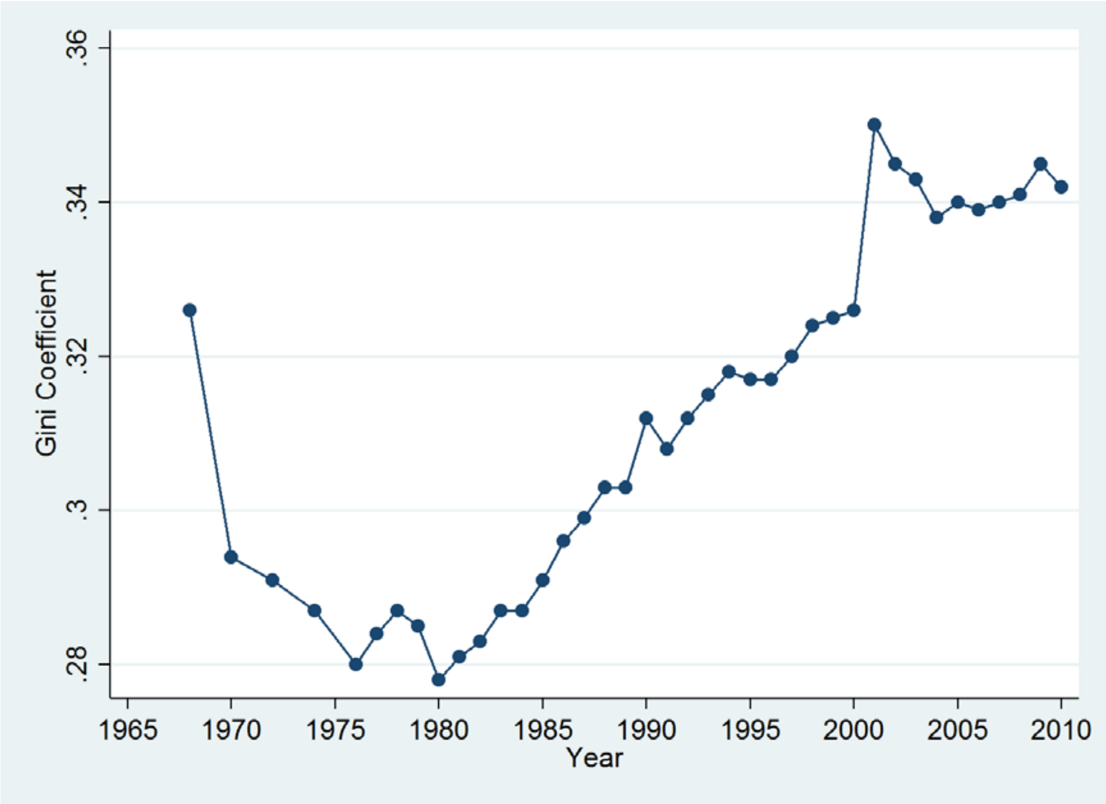

Figure 3: Gini Coefficients of Disposable Household Income in Taiwan, 1968–2010.

Note: Gini coefficients are unavailable for the years 1965–1967, 1969, 1971, 1973, and 1975. They are from the 2012 Report on the Survey of Family Income and Expenditure.

Appendix Table A1: Summary of Kan et al. (2015) and Sun and Ueda (2015)

Paper	Primary sample	Sons' age	Fathers' age	Earnings predictors	Secondary sample	Two-sample IGE estimate
Kan et al (2015)	1988-2006 SFIE	26-45 (avg. = 30)	42-64 (avg. = 57, co-residing with sons)	Years of education, age, and their interactions	1978-1988 MUS (ages 31-55 working males)	All cohorts: 0.18 1943-59: 0.19 1960-63: 0.22 1964-69: 0.21 1970-74: 024 1975-80: 0.22
Sun and Ueda (2015)	2004-2008 PSFD	30-60 (avg. = 42)	Not reported	Levels of education and current occupations	1998 PSFD (estimation sample not reported)	All ages: 0.25 30-39: 0.13 40-49: 0.30 50-59: 0.36

MUS: Manpower Utilization Survey
PSFD: Panel Study of Family Dynamics
SFIE: Survey of Family Income and Expenditure

Appendix Table A2: Estimates of Intergenerational Earnings Elasticity and Rank-Rank Slope in 2005–2010 Using MUS sample

	(1) All Predictors	(2) Industry & Occupation	(3) Education & Industry	(4) Education & Occupation	(5) Industry	(6) Occupation	(7) Education
				Linear Regression			
IGE	0.431***	0.387***	0.462***	0.432***	0.394***	0.386***	0.695***
	(0.050)	(0.049)	(0.058)	(0.050)	(0.059)	(0.050)	(0.092)
				Interval Regression			
IGE	0.425***	0.383***	0.453***	0.427***	0.382***	0.383***	0.687***
	(0.048)	(0.047)	(0.053)	(0.048)	(0.056)	(0.048)	(0.084)
				Poisson Regression			
IGE	0.438***	0.394***	0.449***	0.446***	0.355***	0.400***	0.673***
	(0.060)	(0.059)	(0.066)	(0.060)	(0.069)	(0.059)	(0.090)
				Rank-Rank Regression			
Rank	0.282***	0.259***	0.276***	0.283***	0.192***	0.249***	0.303***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)	(0.030)	(0.033)
Obs.	1,299	1,299	1,299	1,299	1,299	1,299	1,299

Note: The secondary sample consists of working males aged 40-55 from the 1978-1982 Manpower Utilization Survey (MUS). Bootstrap standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A3: Estimates of Rank-Rank Slope by Metropolitan Status in 1990–1994 and 2005–2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1990–1994 TSCS				2005–2010 TSCS			
	Live/Born in Metro.	Live/Not Born in Metro.	Not Live/ Not Born in Metro.	Not Live/ Born in Metro.	Live/Born in Metro.	Live/Not Born in Metro.	Not Live/ Not Born in Metro.	Not Live/ Born in Metro.
Rank	0.385***	0.194***	0.253***	0.267	0.153**	0.189***	0.244***	0.206
	(0.049)	(0.043)	(0.032)	(0.181)	(0.061)	(0.065)	(0.039)	(0.225)
Obs.	425	497	1,136	40	342	204	712	42

Note: The estimates are from rank-rank regressions. Fathers' earnings are proxied by average occupational earnings as in columns (1) and (5) of Table 8. Bootstrap standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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