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Lawrence Dacuycuy

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For comments, suggestions and further inquiries, please contact:
Room 347, School of Economics, University of the Philippines, Diliman, Quezon City
+632-927-8009 +632-927-9686 loc.334 http://www.hdn.org.ph

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Lawrence B. Dacuycuy
De La Salle University - Manila

1. Introduction

Assessing social mobility, the ability of individuals to achieve better social status relative to their parents, provides a good opportunity to evaluate the role of public policy, identify family circumstances that merit effective intervention and ascertain or measure the effects of key labor market developments.

For a developing country like the Philippines, the challenge of enabling intergenerational transmission of family attributes that mitigate poverty and promote equality of opportunities remains a daunting task given existing labor market structures and inequality. Recognizing that intergenerational links between parents' human capital and offspring's labor market performance do matter and this line of thinking necessitates discarding short-termist and incoherent strategies or interventions.

Examining labor market outcomes involving parents' human capital has received sustained academic interest. Limited wage mobility may be the result of a confluence of factors. Facing credit constraints, poor households may infuse inferior investments in human capital and plausibly provide suboptimal parental inputs, thereby limiting economic opportunities of children in the labor market. Assuming that heritability of traits is high in such households, coupled with binding credit constraints, the effects of parents' social status may be persistent, thereby limiting mobility. On the other hand, through higher investments in a child's human capital and provision of optimal parental inputs, richer households can enhance the persistence of quality educational outcomes which translate into better labor market outcomes. Thus, labor market outcomes such as occupational choices, wage inequality and returns to education not only depend on the attributes of workers themselves but are also strongly affected by family background.

We zero in on some issues of importance using simple methodologies. First, we ascertain the degree to which intergenerational mobility can be measured using available survey data. The Philippines does not have a survey data explicitly done for undertaking mobility studies. Thus, we need to determine whether or not there is informational value that can be derived from available datasets. Of particular interest is the constitution of parent – offspring data pairs. Second, using a simple regression – based approach, we determine the extent to which wages are persistent on the part of sons and daughters relative to fathers' wage outcomes using methodologies that are applicable even in the analysis of a single cross section. While bias is still expected, one of the objectives is to empirically characterize lower and upper bounds inferred from OLS and IV model based estimates. We take cue from the literature's emphasis on sample selection rules which largely determine the magnitude of estimated elasticity estimates. Third, we highlight the role of parental education and in a simple empirical way, measure how the labor market rewards or penalizes labor market participants

on the basis of educational attainment of fathers. Fourth, because of the importance of education and the prevalence of measurement issues involving wages, we examine the statistical importance of parental educational achievements relative to their children using a nonlinear probability model, thereby deviating from the usual linear representation of various relationships and using valid proxies for child and parent's permanent incomes. The model set - up easily allows us to examine statistical disparities in educational outcomes conditional on parental education, poverty status, household resources and other determinants. Fifth, we examine if our sample data pairs exhibit selectivity in terms of employment and how selection would affect the elasticity estimate.

Examining whether or not wage persistence is present among Filipino workers remains an important first step in evaluating trends in the labor market. As far as we know, limited evidence for the Philippines has been offered on how family background (proxied by parents' education) affects wage outcomes and enhances mobility.[1] In this paper, two levels of analysis will be provided. First, using a series of cross sections from the Labor Force Survey (LFS) we provide estimates showing the empirical relationship between child's wage outcomes and father's socio – economic status. We will also calculate wage – based persistence measures to understand how the labor market rewards or penalizes wage earners relative to a reference category. Second, we utilize the 2006 and 2009 waves of FIES merged with LFS this allows us to specify a nonlinear probability model to estimate a measure associated with intergenerational education persistence.

The paper finds wage persistence, which can be asserted as one of the central characterizations of the labor market. Returns to education among the well – educated remain high but parental education continues to determine the relative magnitudes of wage gains and losses. Children of highly educated fathers expectedly reap wage gains while those whose fathers have finished no more than high school education suffer from wage losses. With the father's wage distribution used as a reference, daughters are less mobile at the top quintile compared with their male counterparts.

Aside from examining intergenerational wage elasticity, the paper also estimates the degree of educational persistence, which measures the correlation between parental and children's educational achievements. Modeled using a nonlinear probability model, the study finds varying degrees of persistence between the respective educational achievements of children and parental education. To a large extent, parental education profiles determine a child's educational achievements. Results indicate that children with college educated parents tend to graduate from college with high likelihood of success. Again, parental education effects on daughters' chances are better than sons. In terms of resources, remittances will only boost the probability of being a college graduate, with the rest of the education outcomes registering negative effects. Finally, consistent with the literature, children from non – poor households have higher likelihood to graduate from high school and college compared with their counterparts from poor households.

[1] An exception to this is Lanzona's (1998) excellent study that focused on the intergenerational education elasticity, which was operationalized through the estimation of linear models using children – parent pairs derived from a Bicol dataset.

The paper is organized as follows: Section 2 reviews the extensive literature on economic mobility. Section 3 details the econometric methodology, highlighting standard measures of persistence and mobility as well as sources of econometric concerns. Section 4 provides the stylized facts for the Philippine labor market, presents some mobility estimates and interprets results. Section 5 discusses important issues in mobility vis a vis labor market developments. The last section concludes.

2. Literature review

Introduction. Underscoring the challenges faced by societies in promoting mobility and fostering equality of opportunities across generations, the literature on intergenerational earnings mobility, or 'the rise and fall of families' as Becker and Tomes (1986) have aptly labelled it, is vast and expanding.[2] The literature encompasses interesting sub – themes showing the various influences of family background and human capital investments (which includes genetic and cultural transmission within households), wealth, early childhood education and skill development (cognitive vs non – cognitive), higher education, legal initiatives like minimum wages, parental leaves, school financing and public policy and labor market interventions on intergenerational social status.[3] The expansion is moving along theoretical and empirical lines, fueled by the search for comparable and reliable estimates and robust theoretical frameworks, both of which are expected to lead to sound public policy debates and prescriptions which are needed particularly in developing countries where mobility is impaired and inequality is highly persistent.[4]

This section details the connections among theoretical constructs, methodologies and empirical issues and results associated with intergenerational earnings mobility and reviews the various themes, particularly the cross – sectional inequality and mobility link.

Theoretical foundations. For research on intergenerational earnings mobility, the theoretical foundations were laid down by Becker & Tomes (1979) and updated in Becker & Tomes (1986), both of which continue to provide the framework and empirical map for a significant

[2] While this literature review focuses first on intergenerational social mobility which is measured on the basis of earnings, we do not lose sight of the importance of the broader research field of social mobility, under which, several measures of social status are proposed. In sociology for instance, occupational status serves as one way of characterizing intergenerational social mobility, that is, whether future generations deviate from their parents' occupational status. So as not to deal with the immense sociology literature, we limit our discussion of occupational mobility to studies that adopt a comparative stance relative to earnings – based mobility studies. For a multidisciplinary treatment of intergenerational social mobility and excellent review of the empirical issues associated with each measure of social status, see Torche (2015).

[3] While this review focuses on the link between intergenerational earnings mobility and labor market outcomes, it is admittedly difficult to ignore the role of family endowment, skill developments that occurred several years prior to labor market participation, degree of earnings inequality, public policies that shaped households' response, to name a few. Corak (2013) emphasize that the interaction between families, labor markets and public policies shape the future of children, the results on intergenerational mobility clearly depend on national context.

[4] For instance, because of relative high immobility in the UK, studies have been conducted to diagnose the causes and policy initiatives or reforms that may result in some improved mobility outcomes. Some professions may be more difficult to penetrate for workers with certain family characteristics (Macmillan).

number of studies.[5] Operating within a neoclassical optimization setting, the theory postulates that households endeavor to improve the welfare of future generations by investing in human capital. While the model is tractable, it discusses complex human processes. For instance, the degree to which heritability of traits or endowments of capital, ability, and genetics is achieved determines the labor market status of future generations.[6] In its simplest form, the model relies on a combination of investment decisions and a model of intergenerational ability transfer to produce a model of intergenerational ability (Grawe & Mulligan, 2002)[7]. In this very basic model, there is no role for family characteristics, only child ability that is supposed to be randomly assigned. However, in a more encompassing model structure, it is capable of incorporating intra household influences, which are already proven to exert considerable effect on a child's development. Because of the significant influence of credit constraints on household's ability to invest in human capital, researchers have been keen to identify patterns associated with credit constraints – mobility relationships across household subpopulations (Grawe & Mulligan(2002); Becker & Tomes (1986)).

A theoretical enhancement was made by Solon (2004) by allowing the model to explain temporal and locational variation in intergenerational earnings mobility. As Corak (2013) noted, Solon's (2004) interpretation of education returns can be considered indicative of the extent to which labor market inequality impacts intergenerational mobility. Solon's (2004) model also shows that steady state cross sectional inequality responds positively to the presence of stronger heritability, more productive human capital investment, higher returns to human capital and less progressive public investment in human capital (Solon, 2004, p.8).

As noted in several studies, the US exhibits a case of stagnant mobility but increasing cross – sectional inequality due to labor market developments.[8] This is indeed a stylized fact worth establishing theoretically. In terms of new theoretical developments, a model that is able to explain limited mobility in the top and bottom parts of the earnings distribution in the presence of sustained cross sectional inequality was developed by Becker, Kominers, Murphy, & Spenkuch (2015) [henceforth BKMS]. Offering far richer empirical implications, the model makes key connections between labor market outcomes and intergenerational mobility. It provides a formal theoretical explanation why the US experiences low mobility given significant increases in cross – sectional inequality.Some important observations are noteworthy. First, education returns are not constant and considered as one of the main

[5] As Corak (2013) mentioned, the mentioned studies provide the basis for interpreting some of the variables as having causal effects on intergenerational inequality and mobility.

[6] The definition of children's attributes as quoted by Corak (2013) and Solon (2004) from Becker and Tomes (1979, p. 1158) is "children's endowed are determined by the reputations and connections of the families, the constitutions of their families, and the learning, skills, goals, another family commodities acquired through belonging to a particular family culture. Obviously, endowments depend on many characteristics of parents, grandparents, and other family members and may also be culturally influenced by other families."

[7] It should be emphasized, however, that this simple model may not reflect persistence in human capital investments in rich and credit constrained households, making them relatively immobile.

[8] The relationship, known as the Gatsby curve, shows that inequality tend to be negatively related to intergenerational earnings mobility. Thus, the US experience has become a source of academic curiosity.

drivers of inequality. Second, the contention that rising returns to education leads to greater mobility does not happen all the time.

As an innovation, the paper of BKMS embeds complementarities between parental investments and human capital in the production function of a child's human capital, thereby enabling the theory to explain nonlinearities in the production function. This assumption turms out to be instrumental in explaining the US experience, supporting the observation that immobility is experienced in the top and bottom parts of the distribution and mobility is more likely to be experienced in the middle. By introducing complementarity, richer households tend to invest more in their children's human capital even under perfect capital markets. In contrast, because of the higher returns to human capital in households facing binding credit constraints, poorer households tend to invest more in their children's human capital leading to a high degree of persistence. The consequence of persistence characterizing the human capital investments of rich households and credit constrained households results in the enhanced ability of earnings to predict the economic status of children. The same assumption can also be used to explain why even after labor market developments such as increases in returns to education may result in no improvements in intergenerational mobility.

On empirics. Typical of economic theory with empirical content, an offshoot of Becker & Tomes (1979) is a simple way to measure the degree of correlation between incomes of parents and their children.[9] Usually implemented using a regression model, the key parameter of interest, known as intergenerational earnings elasticity captures the degree of responsiveness (average percent change in children's earnings given a one percent change in parental income) of a child's earnings to his/her father's earnings.[10] The magnitude and degree of significance of the parameter estimate is of utmost empirical value. Upward mobility is associated with a lower correlation while persistent transmission of labor market status is associated with a higher correlation.[11]

With all empirical innovations addressing sources of bias, it is not surprising that a large number of studies dealing with intergenerational earnings mobility is observed in countries that put emphasis on the continued collection of longitudinal data. Because one measures the degree of mobility by relating the earnings of one generation of workers against their fathers',

[9] In 1992, Zimmerman noted that the intergenerational earnings elasticity should be interpreted as a structural parameter considering that it can be derived from an underlying economic model. This was actually rationalized by Solon (2004) who showed that the linear model is a reduced form derived from an underlying economic structural model. The said reduced form is evaluated at the steady state. (Becker, Kominers, Murphy, & Spenkuch, 2015) have shown that the relationship may no longer be linear with the assumption that parental investment and human capital are complementary inputs in the production of a child's human capital.

[10] As noted, the estimate may be sensitive to the relative variability of the dependent and independent variables. Suppose the estimate is 0.40. Then a 10% difference between two parents' incomes will translate to 4% difference in the earnings of their respective sons/daughters.

[11] Not to be confused with causal analysis, the estimate represents a correlation which is just a measure of association.

dynamics should be tracked carefully by using panel data.[12] Solid empirics depends on matching families that belong to dynasties.[13] The depth of previous reviews of studies done by Solon (2002); Lee & Solon (2006), Black & Devereux (2010), Corak (2013) and D'Addio (2007) do confirm that US and Europe have advanced the understanding of mobility.[14]

As a global measure based on a stochastic model, the parameter has been subjected to rigorous and robust econometric evaluation.[15] This is normally expected of single – equation models because of the importance of ascertaining the degree of parameter uncertainty, understanding sampling variation and designing robustness tests for inferential validity. Other econometric issues to address include classical measurement errors that may or may not age – related, value imputations to account for unavailable earnings data, transitory fluctuations in earnings, aggregation issues, and life – cycle bias.

While panel data contain dynamic information, some empirical decisions need to be made. We know that earnings are perturbed by economic shocks occurring at some points in the worker's work history, which deviate from permanent income. Transitory earnings changes may be reflected by the data used in measuring mobility but may no longer be replicable in other periods. This leads to biased estimates.[16] Its remedies include using datasets with longer work histories and accurate income reporting such as those found in administrative and tax data and one needs to resort data averaging to reduce the bias (Mazumder (2001); Zimmerman (1992); Ueda (2013)). Life cycle bias refers to the wedge between current and lifetime earnings. This points to the importance of timing of measurement since earnings of workers observed during their early careers will yield low mobility estimates.

One advantage of dealing with parametric models is ease of interpretation, which naturally gives rise to clear policy implications. The sheer frequency of studies that estimated the intergenerational earnings elasticity left something that researchers in other countries desire - a verifiable set of metadata on elasticity estimates. This has led to revisions and now, one can say with high degree of confidence that the US is believed to be less mobile compared to

[12] Grawe & Mulligan (2002) note that because the methodology simply compares the respective incomes of persons observed in two periods of time, it is possible that shocks that affect different generations may have implications not captured by the usual methodology.

[13] Another alternative which relaxes this requirement significantly has been developed by (Bjorklund & Jantti, 1997). In the absence of earnings data for fathers, what they did was to estimate a Mincerian model using another sample that comes from the same super population as the current one. The estimates are then used to predict the earnings of fathers and regress their sons' earnings accordingly. This method is known as a two – sample, two – stage model.

[14] D'Addio (2007) focused on the OECD.

[15] Since the elasticity estimate remains invariant to different values within the domain of the log of parental earnings, it is not robust to distributional misspecification as well as nonlinearities, the latter can be adequately modelled by quantile regression models which conditions the log of child's earnings on parental income and other characteristics at different quantiles in the earnings distribution.

[16] In short, when sample points are selectively chosen to compare parental to children's income, the data generating process may deviate from a model that utilizes all sample points. Thus, a single data generating process may not be representative of other periods contained in the panel.

Nordic countries at 0.40.[17] Differences in estimates depend on the period studied and sample selection rules. However, even after controlling the dataset, divergent estimates still remain not because of methodologies, which are quite uniform, but mainly because of how efficiently datasets were used. Lee & Solon (2006) argue that divergence in mobility estimates may be primarily attributed to imprecise estimation stemming from inefficient use of panel data. In their paper, they show that downward biased estimates will be generated when the sample becomes limited to target cohorts.[18]

In a remarkable paper, Ueda (2013), used nonparametric regression analysis to show that limiting analysis to a global estimate may miss shifts in mobility estimates which are better represented by functionals to deal with nonlinearities. Moreover, he used simulation based methods to minimize the effects of measurement error, a common problem in estimating mobility measures. Without assuming a linear specification for the conditional mean and regressing the logarithm of son's earnings to the predicted log earnings of fathers, he finds that economic opportunities faced by sons from low income households are similar to their counterparts from middle income households.

While the international norm highlights the critical role of data and measurement using panel data, it does not mean that one cannot estimate mobility measures without panel data. There is a literature strand that focuses on the estimation feasibility of using one – time cross sectional data (Ng, Xhen, & Ho, 2009). These employ selection rules that attempt to match the structure of panel data in the US for a single year. Other data features that such methodology has accounted for are the lack of independent reporting of parental incomes, data based on intervals and limited sample size. As noted above, however, biases will still be present and dynamics pertaining to labor market behavior and other adjustments may not be taken into account, thereby limiting the value of inferences derived from such estimates.

On international comparisons. While intra-country estimates remain informative, the insights generated would be incomplete without referring to other country estimates.[19] In the literature, comparative studies on intergenerational mobility exists and more often than not, the comparison is made relative to US and European country experiences. As noted in Solon (2002), intercountry comparisons impart valuable lessons as to how unique institutional arrangements and economic environments in the respective countries influence mobility outcomes.

Comparative analyses generally yield contrasting results. Azevedo & Bouillon (2010) analyze and compare Latin American experience with the US and other European countries and find

[17] Zimmerman (1992) correctly pointed out that the presence of measurement errors in data on long run economic status will result in downward biased estimates. This study effectively reverse the previous finding of high mobility in the United States.

[18] Following their analysis, consider constituting a cohort of children born between the years 1950 and 1970. For each cohort, elasticity is estimated when children reach the age of 25. Thus, this means that the elasticity estimates for 1985 will be based on cohorts born in 1960 but all data for 1985 will be ignored.

[19] Admittedly this may be more meaningful for developing economies who may want to emulate some of the reforms identified as mobility – enhancing in more developed economies. However, we also cannot discount the possibility that developed economies will also learn from their counterparts.

that Latin American countries are characteristically and generally immobile. European countries on the other hand, continue to offer a glimpse of how their economic systems contribute to relatively better mobility profiles compared with the US. Azevedo & Bouillon (2010) point to the importance of earnings distributional dynamics as one way to understand earnings mobility. They show that relative to Nordic countries and even the US and UK, countries like Chile, Brazil and Peru registered higher intergenerational income elasticity estimates, indicating relative immobility.

Concerned with the connection between social mobility and cross – sectional inequality, Bjorklund & Jantti (1997) contrasted Sweden's degree of mobility with the US and found that Sweden emjoys a higher degree of mobility.

In comparing Germany and the US, Couch & Dunn (1995) found that earnings correlations between children and their fathers are somewhat similar or identical despite different societal structures and labor market experience. On the other hand, the earnings correlations between children and their mothers appear to be much weaker Germany than in the US.

It is not always that case that the US is peerless when it comes to its record of relative immobility. Claiming that due to the similarities in economic structures and policy environment, Ng, Xhen, & Ho (2009) showed that Singapore replicates the US degree of immobility.[20] They argued that Singapore shares some of the US characteristics when it comes to educational, labor and welfare systems which work together to promote competitiveness but less emphasis on more progressive policies is observed. In a report by OECD, the US, Italy, France and UK showed high intergenerational earnings elasticity. The report also showed that the earnings ability of individual workers is strongly associated with fathers who achieved tertiary education. Intergenerational wage persistence is observed for some southern European states.

Distributions, data processes, and sample selection. It appears that the literature also shows that one should pay attention to data generating processes specific to respective countries being compared.[21] Country – specific wage distributions evolve differently over time and across space, continuously shaped by market forces and policy makers. Comparability may hinge on the presence of nonlinearities and the way sample selection rules are designed. Assessing the evidence for Nordic countries, Bratsberg, et al. (2006) prove that estimates are not entirely linear throughout the earnings distribution compared with the US and UK. A distinguishing feature however, is that linearity is present in the lowest portion of the distribution and linearity is observed for the higher percentiles.[22] Beller & Hout (2006) observed that the US is mainly immobile at the top and bottom of earnings distribution. In a study on Brazil, Ferreira & Veloso (2006) demonstrated how nonlinearities allows one to

[20] Using a one – point cross sectional data to replicate sample selection rules employed in studies on developed economies, this study is interesting in the sense that due to data limitations, issues on comparability, estimate attenuation and other forms of bias were present.

[21] Using methods that are data driven may be better as long as there is still uncertainty as to the nature of data generating process.

[22] This is one function of robustness checks, that is, to ascertain whether or not log of parental income exerts a uniform influence on sons' or daughter's income. the presence of nonlinearities may also be associated with credit constraints as explained in (Grawe & Mulligan, 2002).

validate the role of borrowing or credit constraints which are translated in the form of mobility patterns in favor of richer households who do not experience binding credit constraints.

It is known that sample selection rules spawn different results especially in mobility analysis. In many studies, the usual treatment of zero earnings or incomes is to exclude samples associated with them. While previous studies ignored the effects of unemployment, evidence linking labor market outcomes such as long – term unemployment and earnings mobility is provided by Drewianka & Mercan (). Driven by the need to clarify sample selection rules, the paper finds that correlation increases when long term unemployment spells for both father and son are taken into account as part of sample selection rules. This shows that unemployment may introduce more persistence to households that already face credit constraints and may limit the mobility of middle income households as well. Their results confirm that estimates will be close to those in the literature when zero earnings are excluded from the sample, thereby highlighting the sensitivity of estimates to sample selection rules.

Public policy. Differences in intergenerational earnings mobility are influenced by a lot of factors. As explained in Azevedo & Bouillon (2010), workers endowed with human capital enter a labor market, the conditions of which may be different from what their parents have experienced. One of the main determinants of earnings mobility is education returns, which is also associated with earnings inequality. Ferreira & Veloso (2006) note that for Brazil, a determinant of mobility is the intergenerational transmission of education. As explained in Beller & Hout (2006), international differences in occupational mobility are attributed to educational inequality, namely, the share of adults who attend college and equality of educational equality.

As shown in previous studies highlighting the presence of nonlinearities, ignoring distributional properties through the implementation of sweeping policy initiatives may be ill – advised in mitigating the impact of low mobility.[23] Aside from cross – country analyses, it is also important to take note of robustness patterns across location and subpopulations within countries. Patterns can be established for mobility and poverty has been known to contribute to less mobility by introducing credit constraints. Ferreira & Veloso (2006) showed that for rich areas in Brazil, the degree of mobility is higher compared with poorer areas.

Even with robust human capital, returns to education are not guaranteed since it depends on the dynamics of interaction between demand and supply of skills, labor market discrimination and segmentation.[24] Institutional factors such as minimum wage legislation, initiatives that improve the transmission of skills at an early age, educational policies, and economic growth. In the discussion of mobility, one of the key factors is government policy

[23] An interesting example involves the hollowing out of the UK labor market. The implications on policies dealing with mobility are obvious. As noted in Crawford, Johnson, Machin, & Vignoles (2011), it would be better to focus on programs that promote mobility for those located in the middle of the earnings distribution than those that linger in its lower portions when cost – effectiveness is considered.

[24] A good example is provided by Laurison & Friedman (2015) who showed that achieving high educational attainment is not sufficient for earnings mobility especially when discrimination is present in UK's elite occupations.

and programs and this is where the theoretical framework is needed. BKMS note that the degree of complementarity between parental inputs and parents investments and government programs would largely dictate the movement in mobility. Programs that complement parental inputs crowd in rather than crowd out investments by parents. In contrast, the picture may be altered if they are complementary to parents' investments. In a paper, D'Addio (2007) concludes in her review that countries with higher income inequality and returns to education end up having lower intergenerational earnings mobility.

Another important determinant is education policy which was shown as an important source of independent variation in parental ability.[25] While education indeed affects mobility, the direction may not always in favor of achieving better mobility outcomes especially when its interaction with public policy yields unintended results (Corak, 2013). For instance, Machin (2004) concluded that UK's educational system may be responsible for preventing increased mobility by reinforcing inequalities by enabling children from richer households to benefit from educational reforms, far better than those who belong in poorer households. Such experience certainly highlights the role of educational policy in improving mobility. Beller & Hout (2006) observed that progressive public polices in Nordic countries may help low income parents send their children to college.

Lesser mobility can be caused by higher educational returns and less public financing. As explained, with limited public spending, poorer households will have limited educational opportunities and may have difficulty reaching college. Thus, with increasing returns to education, it is expected that earnings inequality will rise and the limited educational opportunities will result in lesser mobility. In the OECD report, wage persistence, defined as the distance between the estimated wage of individuals whose father had achieved tertiary education and the wage of an individual whose father had achieved below upper secondary education is stronger for sons than daughters (OECD, p. 185).

In a more engaging study that directly allows the influence of institutions on intergenerational wage mobility was written by Causa, Dantan, & Johansson (2009). Essentially, it tries to understand whether or not the introduction of redistribution and income support policies and labor and product market institutions do have effects on mobility.

Wage distributions and mobility. While the preceding discusses important empirical issues concerning the intergenerational earnings elasticity, there is also a line in the literature where earnings mobility is linked to the inequality in the distribution of earnings.[26] The main point of interest is to find out whether or not earnings mobility can affect the state of earnings inequality.

In some of the papers, the degree of mobility can be measured without relying on the regression framework. Rather, given panel data, one can compute for summary measures that are associated with inequality at various parts of the earnings distribution and mobility.

[25] Black, Devereux, & Salvanes (2005) provide an interesting study on the effects of increasing the number of years of mandatory school in Norway.

[26] Apparently, inequality analysis will not be able to provide explanation as to why a certain group of workers will reach different points of the earnings distribution over time relative to other groups.

Greater mobility promotes equality.[27] Buchinsky & Hunt (1996) developed mobility – based measures and examined wage mobility dynamics in the US in order to explain earnings inequality at different time horizons. They were able to show that one plausible reason why the inequality exploded in the 80s is due to falling mobility.

Bachmann, Bechara, & Schaffner (2012) decomposed inequality and mobility measures for countries belonging to the EU into within and between group components. Results were largely heterogeneous. Mobility was found to reduce inequality. A study in Turkey provides a list of factors that may be connected to wage inequality and wage mobility. (Tansel, Dalgic, & Guven, 2014) explained that poor mobility of workers especially from the lower part of the wage distribution may be caused by weak institutionalization of the labor market.

Learning from the sociology literature. We will make a quick turn towards the rich and useful sociological literature on intergenerational social mobility, which focuses on occupational mobility. Again, the US and Europe both lead in examining measurement and other issues that link occupational mobility and intergenerational dynamics.

Starting off, Beller & Hout (2006) were right in saying that occupational status and earnings when used to proxy for intergenerational social mobility answer different questions. But this does not mean that they should not be used alongside each other. As explained in Beller & Hout (2006), one way to characterize occupational mobility is to categorize occupations into a few classes and from there measure the extent of class immobility, downward mobility and upward mobility between generations (p. 23).

The use of occupational status data has several advantages. It can easily allow the estimation of intergenerational occupation correlations largely reflects the existing methodology used in standard analyses of earnings mobility. Torche (2015) notes that data on occupation is readily available and is not subject to recall bias compared with earnings.[28] This renders feasible estimations that pit a son's occupation to his father's. Assessing occupational dynamics can uncover characteristics of labor market such as the hollowing out of middle jobs in the UK markets. Knowledge of these dynamics can inform policy.

The simplicity may have negative implications on the degree of interpretability, however. As Torche (2015) has explained, the variable occupation is not free from measurement errors and sometimes the kind of inference is not as clear cut as when earnings is used to measure social status. This is because when occupational mobility is assessed, there should be a representative profile that acts as a reference. In contrast to the distributional assumption usually imposed on earnings, there is also the uncertainty as to how the distributional characteritiscs of occupational status will affect estimates and the degree of usefulness when

[27] This literature thread is reminiscent of the development and wide utilization of inequality measures that can be decomposed into subpopulations. Examples include the Gini coefficient, Theil inequality index and mean log deviation. The advantage is that they are easy to compute and interpret and can be used to track changes in mobility and inequality over time.

[28] There are studies that deal with missing data on earnings, especially on the part of fathers. A two – stage instrumental variables method is used to impute the earnings of fathers using a linear model with education, occupation, and other key variables as determinants. On the basis of estimates, the earnings of fathers in matched father – son samples will be predicted (Azevedo & Bouillon, 2010).

subpopulations are taken into account.[29] As shown in the study of Ganzeboom, De Graaf, & Treiman (1992) and Ng, Xhen, & Ho (2009), the use of occupational prestige indices provides an alternative way of exploiting the informational content of occupation when integrated into the modeling structure.

What do the evidence say on the degree of accessibility or relative openness of occupations? Laurison & Friedman (2015) think that while sociologists have focused on the traditional issue of access to certain occupations, one needs not lose sight of their success the moment they are admitted in such occupations. This renders important the consideration of class origins which may act as barriers to intra – occupational mobility[30]. Using British LFS data and relying on a finer disaggregation that can match social origins and examine the relative openess of elite occupations and the earnings of upwardly mobile, Laurison & Friedman (2015) show that tradional professions are easily accessed by children of professionals and higher managers, professionals and those with technical high status. it appears that there is empirical support for the role of occupational backgrounds with those who come from non – elite occupation background tend to have slower wage growth or disadvantaged compared to their counterparts who have elite occupational backgrounds. This evidence pinpointing discrimination is important and the authors speculate that for the wage immobile, low levels of social capital may be at fault.[31]

3. Methodology

3.1 Measuring mobility

Our methodologies of choice reflect well – established techniques for estimating the effects of parental backgrounds on children's labor market outcomes. Whether linear or not, the anatomy of estimation strategies reveals a structure that uniformly follows a typical Markov process, thereby comparing present generation's outcomes against their immediate past counterparts. While the availability of true panel data is usually seen as a vital requisite for addressing econometric concerns, there are also other ways through which plausible measures of mobility can be estimated. But one necessary requisite is that a dataset on child – father pairs should be available.[32]

We begin by specifying the equation of interest. Using data on child – parent pairs, the equation shows the variation of the deviation of a child's income from his mean income relative to that of the parent. The parameter β represents a population measure of persistence (or correlation) in the effects of parent's permanent income.

$$y_{i,h}^{c} - \bar{y}^{c} = \beta\left(y_{j,h}^{p} - \bar{y}^{p}\right) + \epsilon_{i,h}^{c} \qquad (1)$$

[29] As noted in Torche (2015), it is not clear why the assumed distribution for occupational status is normality since the said variable is discrete and has finite bounds. Because of the assumption of normality, any inference carried out may be misleading.

[30] This is known as the class ceiling.

[31] This kind of interpretation made by the authors appears to be in close proximity to what Becker & Tomes (1986) highlighted.

[32] One can argue that we can also generate estimates involving daughter – mother pairs. Without controls for identifying the selection probability, we face several forms of bias, such as sample selection bias, attenuation bias and life – cycle bias. Thus results need to be interpreted with caution.

where index h refers to the household both child i and parent j belong to.

Following Ng, Xhen, & Ho (2009), Azevedo & Bouillon (2010), the above equation can be rewritten in the following standard form:

$$y_i^c = \gamma_0 + \beta y_i^p + \epsilon_i^c \quad (2)$$

where $\gamma_0 = \bar{y}^c - \beta \bar{y}^p$. The above model assumes that y_i^c and y_i^p should be observed and the mean of ϵ_i^c conditional on the parent's permanent income is zero.

Because both y_i^c and y_i^p are measured in logarithms, the estimate for β is interpreted as an elasticity measure. If β is equal to 0.5 and parent's earnings exceed the mean earnings of his cohort by 50%, then the child's earnings will exceed his cohort's mean earnings by 25%. On the other hand, suppose that a parent's earnings is lower than his cohort's mean income by 50%. Then a high β means that the child will have income much lower than his cohort's mean income. This means that what gets transmitted to the child is relative disadvantage. A higher β then is associated with lower mobility.

Equation (2) is the fundamental equation for measuring persistence. However, there are a lot of empirical issues. For measuring persistence, the relevant variables should pertain to permanent incomes, something that is difficult to measure in practice. As noted in Ng, Xhen, & Ho (2009) and Bjorklund & Jantti (1997), observed parental incomes include both permanent and transitory components. Persistent transitory shocks can only be accounted for by using panel data which implies that a one – period data fail to address this type of bias. When used, a mismeasured father's permanent income will result in downward biased estimates (or attenuation bias), which may mislead people into believing that there is ample evidence of mobility.[33] Understandably, mismeasurement of the dependent variable does not have the same effect. As explained in econometric texts, a mismeasured dependent variable does not bias the estimate as long as father's permanent income is not measured with error.

Attenuation bias can somewhat be cured by data averaging, which also takes care of persistent transitory shocks. While estimates are downward biased in the presence of limited data, the opposite happens when one resorts to IV estimation. Using education and occupation as plausible instruments for father's permanent income, Bjorklund & Jantti (1997) showed that the resultant estimate would be upward biased given that parental education has a positive effect on son's/daughter's income. As noted in Bjorklund and Jantti, this way of instrumenting for parental income represents a legitimate upper bound on the true intergenerational correlation.

Another IV based method that is used in instances where earnings data on fathers are missing is the Two sample instrumental variables (TSIV) estimaor implemented by Bjorklund & Jantti (1997) and Ferreira & Veloso (2006) for Sweden and Brazil, respectively. A superpopulation of male workers is first constituted and using the structural estimates,

[33] This is exactly what earlier US estimates have mistakenly conveyed – high intergenerational earnings mobility.

earnings or wages of fathers in the main dataset are predicted. The predicted data are then used to determine the degree of persistence.

Aside from measurement – related biases which point to the use of IV estimation as a preferred methodology, accounting for the differential timing in the measurement of earnings for young and old generations really matter. In most surveys, sons' wages or earnings are measured much earlier in their careers than their fathers. Haider & Solon (2006) showed that the correlation between current and lifetime earnings is low when men are in their 20s and close to 1 when they are in their 30s. the result reminds us of attenuation bias if a relatively young sample is used. As also noted in Ng, Xhen, & Ho (2009), parental age also affects elasticity estimates, with estimates expected to become lower for relatively old parents.

3.2 Cross – sectional wage persistence

The above framework is critical in measuring the empirical link between parental and child labor market outcomes. Because of the difficulty in measuring permanent income on the basis of current status, Causa, Dantan, & Johansson (2009) [henceforth CSL] use educational achievements of fathers as a proxy for permanent income.[34] It qualifies as a proxy because of the relative stability of estimates and due to the high degree of correlation between education achievement and wages.

CSL's framework relies on child – parent data pairs and uses the Mincerian model platform to quantify a simple measure for persistence. Closely resembling the general framework for assessing intergenerational mobility, the framework can work with cross – sectional data to generate a measure of wage persistence which relies on how the educational achievement of the father, relative to a base reference achievement, affects the child's wage. It is a legitimate measure because the proxy for permanent income can have permanent effects.

Consider the Mincerian model for the child's wage $lnwage_{i,h}^{c}$.

$$lnwage_{i,h}^{c} = \alpha_0 + f\left(Educ_{i,h}^{c}; \delta^{c}\right) + g\left(Educ_{j,h}^{p}; \delta^{p}\right) + Z_{i,h}'\varphi + \omega_i^{c} \qquad (3)$$

In the model, the child's wage is affected by his level of educational attainment along with other attributes. ω_i^{c} is orthogonal to included covariates and is assumed to be a random stochastic process. $f\left(Educ_{i,h}^{c}; \delta^{c}\right)$ and $g\left(Educ_{j,h}^{p}; \delta^{p}\right)$ are functional components that may or may not be linear.

For all households h, we relate a child's educational achievement to his parent and his or her other attributes or characteristics through the following equation:

[34] The main reason why father's education was used to proxy for permanent income is that their dataset does not contain information on parental income or wages. Though wages or earnings are preferred strictly to other measures that proxy for current economic status, they contend that permanent income is difficult to estimate given data unavailability as much information is needed. As already mentioned, biases arising from the latent nature of permanent income may be transmitted to parameter estimates, thereby affecting their consistency.

$$Educ_{i,h}^{c} = m\left(Educ_{j,h}^{p}; \delta^{p}; Z\right) + \epsilon_{i}^{c} \quad (4)$$

$m\left(Educ_{j,h}^{p}; \delta^{p}; Z\right)$ is a function that is separable in its arguments and may or may not be linear in $Educ_{j,h}^{p}$. It should be worth mentioning that the above equation does not explicitly account for the role of ability as may be measured appropriately by the child's IQ. Based on BKMS (2015), such a reduced form equation may generate upward biased estimates because the ability of the child may be highly correlated with parental human capital. This means, that when substituted as done in CSJ, we would generate biased estimates.

Combining two equations, the outcome is a Mincerian wage function that contains parent's educational achievements.

$$lnwage_{i,h}^{c} = \alpha_0 + f\left(m\left(Educ_{j,h}^{p}; \delta^{p}; Z\right) + \epsilon_{i}^{c}; \delta^{c}\right) + g\left(Educ_{j,h}^{p}; \delta^{p}\right) + Z_{i,h}'\varphi + \omega_{i}^{c} \quad (5)$$

At this point, the specification of generic functional forms does not yield clear parametric combinations. However, it is clear that the variation in the wage of the child now becomes dependent on the educational achievement of the parent, with the effects dictated by the true parameter values of δ^{p} and δ^{c}. The new error structure will now be considered composite, incorporating unknown covariates that directly affect schooling achievement and unknown covariates that directly affect wages.

There are two measures: wage premium and penalty, both of which are attributable to family background. As defined in CSL, "the wage premium is interpreted as the percentage increase in the child's wage of having a father with tertiary education relative to one whose father had upper – secondary education." On the other hand, the "wage penalty is the percentage decrease in the child's wage of having a father with less than upper secondary education related to the one whose father had upper secondary education."

3.3 Educational achievements and parental education: Intergenerational estimates

In view of the shortcomings of wage data to yield unbiased estimates, we employ a methodology that uses both parental and children's educational attainment.[35] This is consistent with the literature's recognition that education has a high correlation with permanent income. Absent are the transitory effects experienced when wage or earnings data are used, using parental education can also allow us to determine the extent to which educational outcomes are partly determined by the transmission of inheritable traits that translate into better labor market outcomes. More importantly, the methodology provides measures (in probabilistic terms) for intergenerational education persistence.

The methodology used is ordered probit which is suitable for analyzing ordered categorical data such as educational attainment. The framework is maximum likelihood based. This deviates from Lanzona (1998) and Behrman, Gaviria, & Szekely (2001) for the simple reason

[35] Being a first order markov process, the structure is similar to the one that is used for wages. This dramatically increases the model's degree of freedom since earnings data may be subject to recall bias and greater likelihood of item non – response compared with education attainment.

that education gets measured as a categorical variable. The advantage of this is obvious. When linear regression model is used, we are assuming that the marginal effect of the years of schooling of either parents is constant throughout the support. For instance, if the coefficient estimate is 0,3 for father's years of schooling, it is uniformly applied to different schooling levels of sons or daughters. This may run counter to the observation that having a son or daughter finished college education may yield higher parental utility, entails much higher costs, and may be associated with qualitative processes involved in the transmission of parental ability.

Inducing numerical transformation may be, to a certain degree, less empirically tenable since no information is provided in terms of the actual start of schooling age and some categories such as high school undergraduate, college undergraduate may not be informative as to the true value of schooling years. When used as independent variable, this may have introduced incurable biases given the dominant correlation between education and the usual regressors that enter the educational attainment regressions.

Similar to CSJ, we use ordered probit model to analyze the impact of parental education on child education outcomes to infer the degree of mobility.[36] We assume that observed educational outcomes are generated by an underlying latent process that may be associated with children's propensity to achieve in education. Let this process $e_i^* = x'\beta + \epsilon$ be an underlying linear stochastic process. Following Greene, we now map all the possible values of a child's education on e_i^*.

$$
\begin{aligned}
e_i \quad &= No\ grade\ completed \quad e_i^* \leq 0 \\
&= Elementary\ undergraduate \quad 0 < e_i^* \leq \nu_1 \\
&= Elementary\ graduate \quad \nu_1 < e_i^* \leq \nu_2 \\
&= High\ school\ undergraduate \quad \nu_2 < e_i^* \leq \nu_3 \\
&= High\ school\ graduate \quad \nu_3 < e_i^* \leq \nu_4 \\
&= College\ undergraduate \quad \nu_4 < e_i^* \leq \nu_5 \\
&= College\ graduate \quad \nu_5 < e_i^* \leq \nu_6
\end{aligned}
$$

where the ν_k represent the cut – off points.

Following Lanzona (1998), we include both father and mother education since it has been shown that in the Philippines, maternal education can have a significant impact on the educational outcome of daughters. Aside from parental education, we control for other variables that may affect the child's educational outcomes. These pertain to the regional residence of the household, urbanity, interaction terms created by interacting regional residence with urbanity, a measure of non-labor income that includes other sources of income including domestic and foreign remittances, household gifts, earnings from financial instruments or investments.

4. Results

[36] We do not create new categories but rather extend analysis to all values of educational attainment variables. This mean that we will be generating probability estimates for all 7 outcomes in the child's educational attainment.

4.1 Stylized facts

While we have become accustomed with the usual labor force statistics measuring labor market outcomes such as employment, unemployment, underemployment, etc., we know little about statistics associated with offspring – parent pairs.[37] To understand some labor market trends, we provide simple labor market statistics that in a way, characterize outcomes for children relative to their parents. We will also look into one - son or daughter households and compare them against those with two - sons or two - daughters. The idea is to at least detect some patterns attributable to differences in household composition. Relying on the urban – rural divide, key outcomes include educational achievements and occupation. This will essentially pave the way for the empirical analysis that will follow. The said analysis hinges on the identification of the impact of parental education, the requisite dataset should come in the form of parent – child pairs.

Occupational categories are aggregated on the basis of two – digit PSOC. The category, farmers is used to collectively denote Farmers, Fishery and Forestry Workers. High grade professionals (HGP) include government and private sector workers who are involved in planning, formulation and implementation of intra – organizational policies. Lower grade professionals (LGP) include workers who assist or implement technical work. Non – manual workers are those that include clerical and service workers. Workers in occupations which require knowledge of industrial processes are classified as Manual Skilled. Manual semi – skilled are those adept at operating power tools but may not be entirely familiar with industrial processes. The last category, Low Skilled include those who are in elementary occupations. This category includes unskilled laborers and agricultural workers distinct from farmers. The educational categories are: No grade completed (NGC); Elementary Undergraduate (EU); Elementary Graduate (EG); High School Undergraduate (HSUG); High School Graduate (HSG); College Undergraduate (CUG) and; College Graduate (CG).

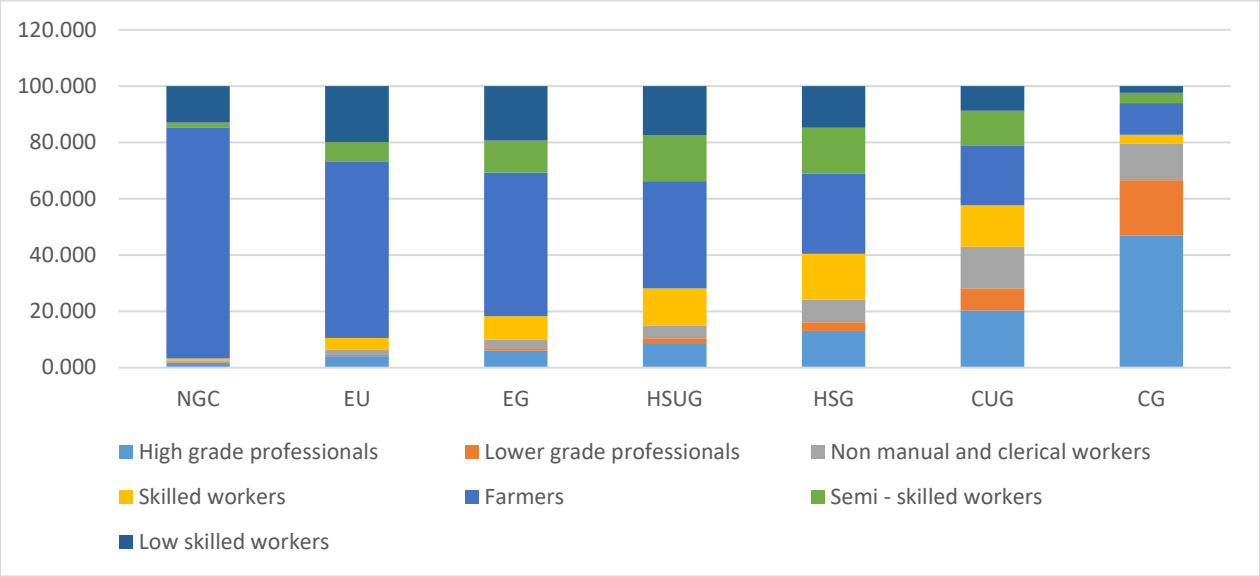
4.1.1 Fathers' occupation and education

Because of the established significant impact of parental education on occupational choices and children's educational outcomes, we start by examining statistics related to father's education and occupation.

Statistical results do confirm that educational attainment, up to a certain extent, is correlated with occupational choices. Spanning 2003 – 2009, it is apparent that a significant proportion of fathers who have not attended college are employed as farmers, fishery and forestry workers. As the education profile of fathers now encompasses college level education, an increasing proportion of fathers categorized as high professionals, lower professional and non – manual workers become the norm. Manual workers of varying levels of skill tend to be more associated with workers who have achieved no more than high school.

[37] Usual labor force statistics will still be presented and discussed though. This time the issue of mobility and the results will serve as the background to facilitate the discussion of how important labor market developments are.

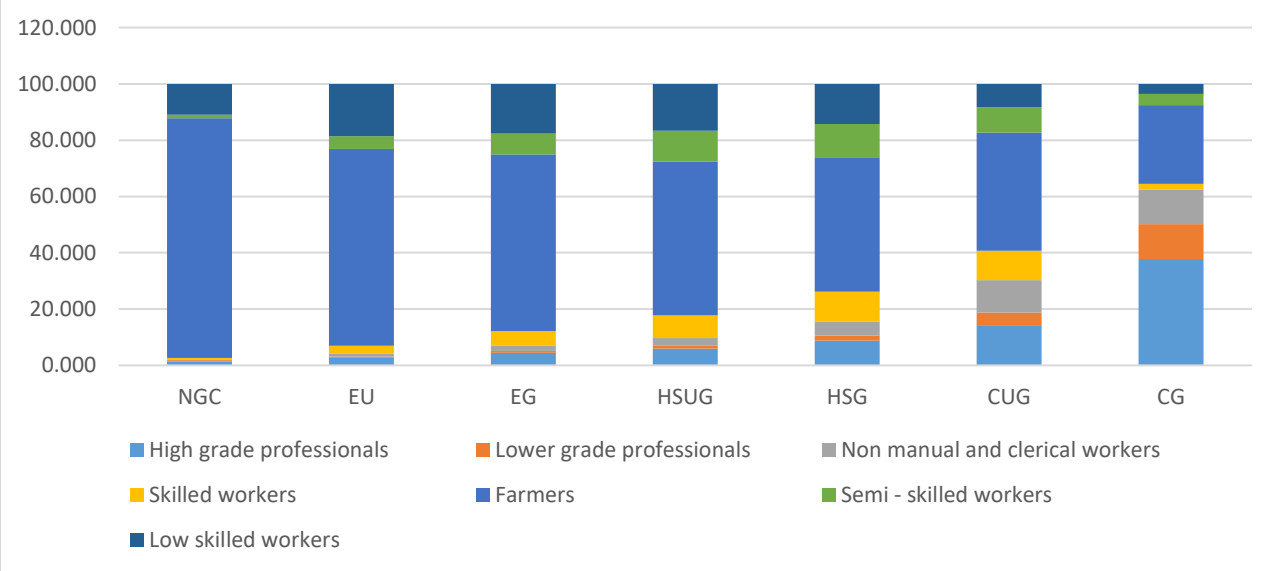
Figure 1 Educational achievements and occupation of fathers: Both urban and rural (in percent)



Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A2.

Because of the significance of the agricultural jobs in rural areas, it is important to provide a contrast between rural and urban based households. The contrast is immediately evident. In rural areas, more than 40% of all fathers whose educational achievement is less than high school are classified as agricultural workers. Aside from this, they are more likely engaged in manual occupations that offer very low compensation. For those who have finished college, more than a quarter still hold farm – related jobs, and more than a third become professionals.

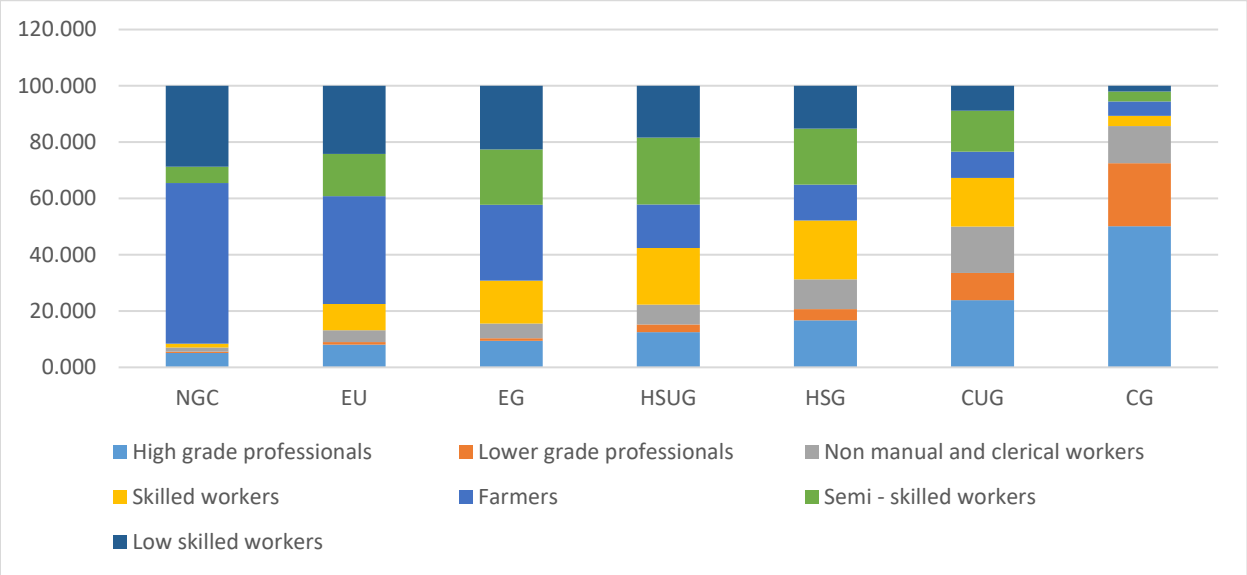
Figure 2 Educational achievements and occupation of fathers: Rural (in percent)



Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A2.

As geographical differences accentuate job heterogeneity, agricultural jobs in urban areas decline as father's education improves. Manual jobs become dominant for workers who have only attended and graduated from high school and it is more likely for college graduates to land in professional jobs or non – manual jobs. Of those who have finished college, less than 50% land on high professional jobs, with almost a quarter holding lower professional jobs.

Figure 3 Educational achievements and occupation of fathers: urban (in percent)



Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A2.

4.1.2 Children's own educational achievements and occupation

There is an interesting set of statistics that shows intergenerational occupational preferences or labor market outcomes as reflected by the proportion of respondents who land in certain occupations relative to a specific educational achievement.

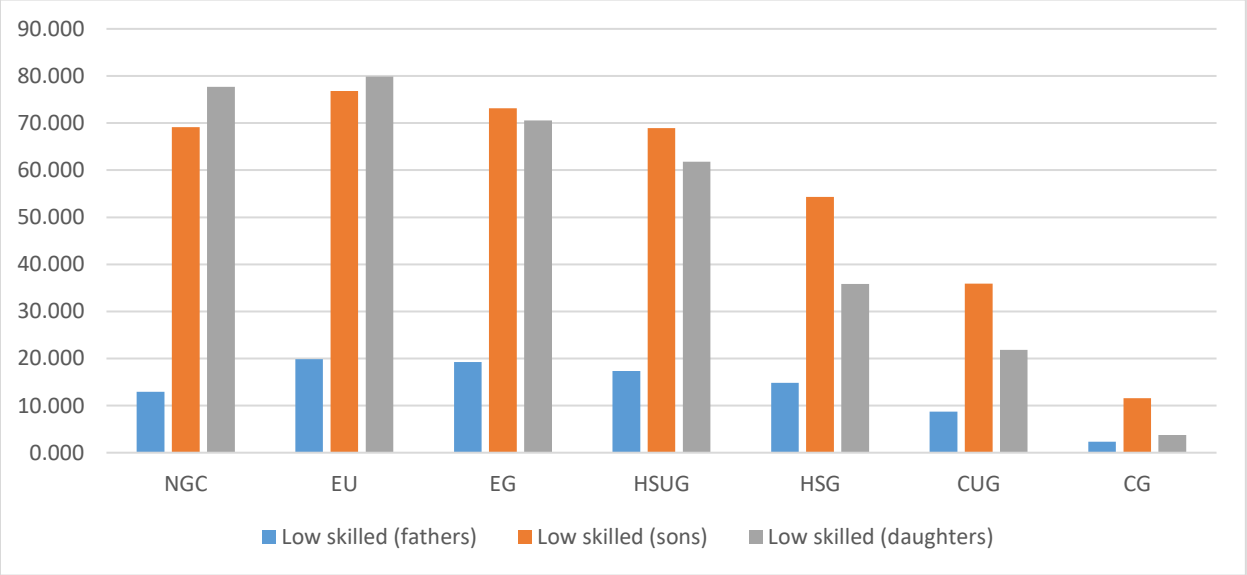
As shown in table A2, fathers who graduated from college tend to land on high grade professional jobs, followed by low grade professionals. In contrast, when we look into sons who also finished college, the proportion is much less, off by close to 20 percentage points. Daughters who have graduated from college performed much better than sons but fall short of their fathers.

In urban areas, 50% of fathers who finish college end up being high grade professionals. In contrast, the sample of sons with college degrees who are considered as such maintain the earlier proportion. For daughters, the relative proportion is almost the same.

Reflecting the availability of opportunities in rural areas, the proportion of fathers who have completed college fell to 37%. While the relative proportion of sons also fell, it is surprising that daughters have maintained their position.

As shown in figure 4, one fact that shows marked differences between fathers and their children is given by the relative proportions of sons and daughters who work in low skilled jobs across educational categories. The results highlight the role of education in determining occupational choices and to a certain extent, trends in the labor market.

Figure 4 Relative proportions of fathers, sons and daughters, by educational attainment



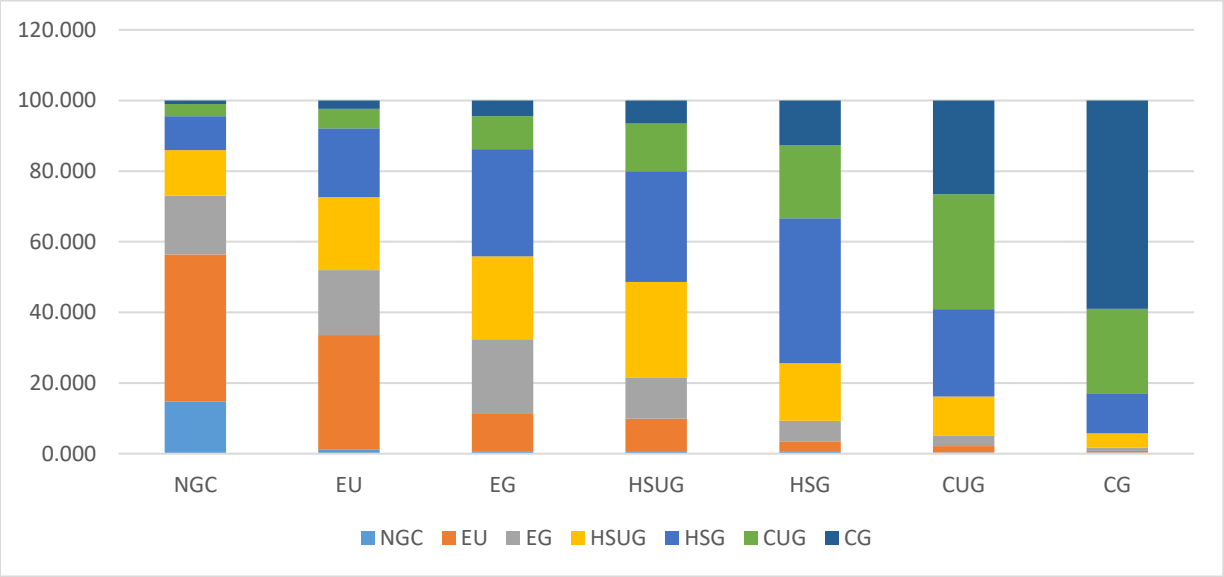
Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A2.

4.1.3 Father and son's education

Do we observe a high degree of association between father and son's educational achievements? The empirical literature shows the importance of the link especially in measuring and explaining educational mobility.

As shown in figures 5, 6, and 7, a father's education is associated with son's improving educational profile. The proportion is moderately high, with more than 40% of their sons obtaining college degrees. Significant proportions of sons achieving no higher than high school diploma can still be observed, though, especially when fathers have failed to complete high school.

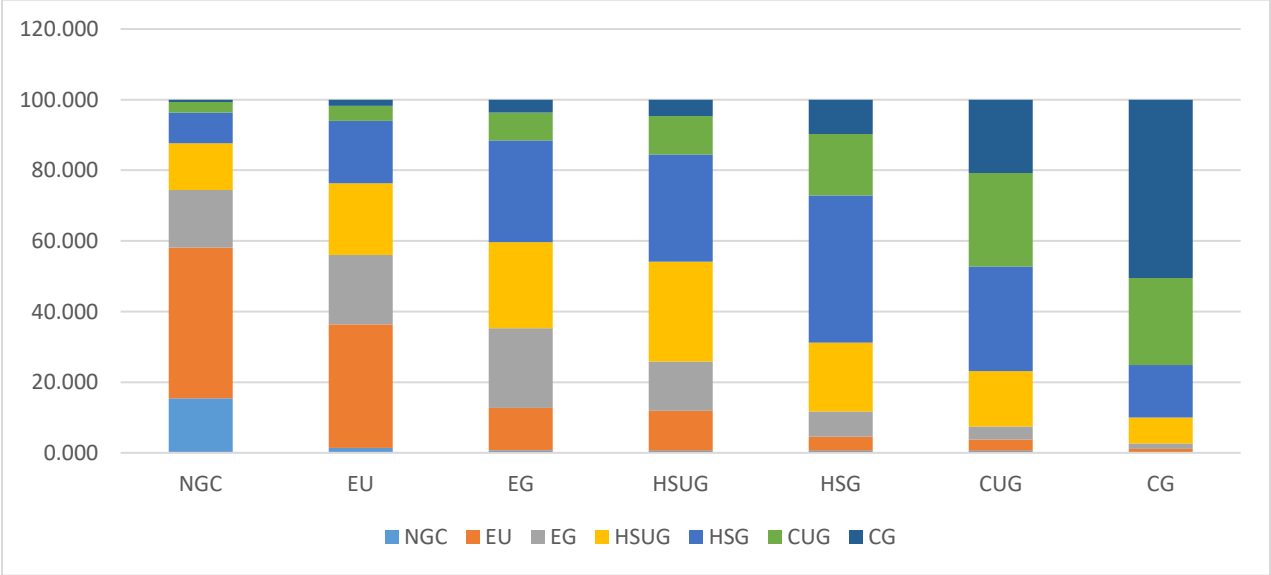
Figure 5 Father and son's educational achievements: Both urban and rural (in percent)



Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A2.

Disparities between rural and urban based fathers are quite large. In rural areas, fathers whose highest educational achievement is no more than high school have very low proportion of sons who have at least attended college. 75% of sons being able to attend college come from households with college educated fathers.

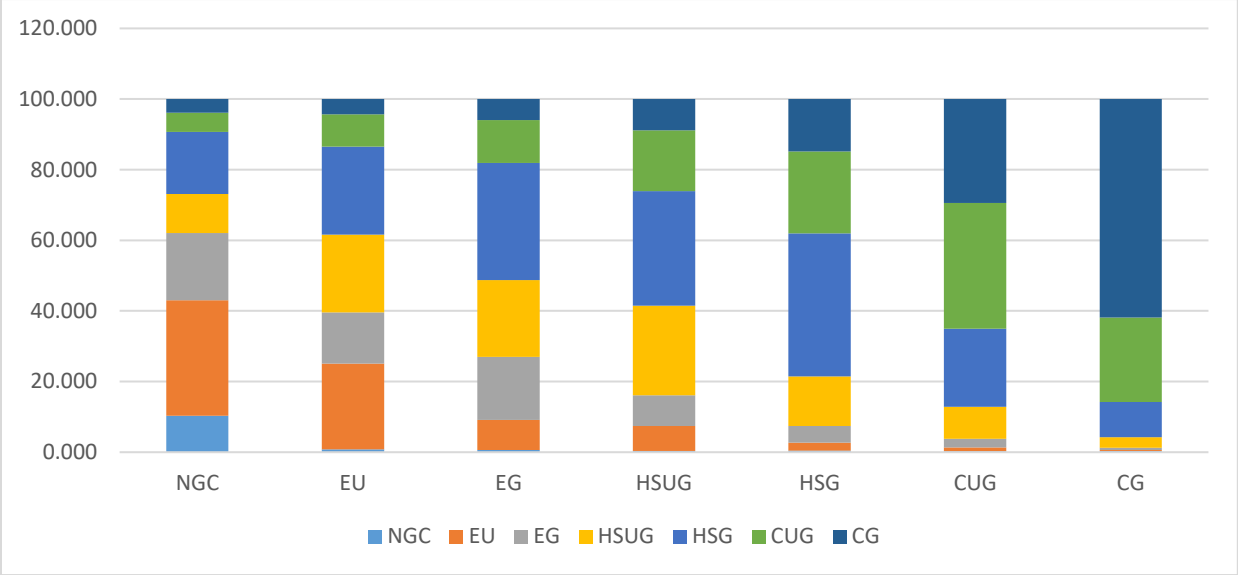
Figure 6 Father and son's educational achievements: rural areas (in pcercent)



Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A2

In urban areas, a big difference has something to do with the profile of fathers who have at least high school diploma. In contrast to households living in rural areas, the proportion of fathers with high school diploma whose sons attended college is 38%. For college undergraduates it's 64% and among college graduates it's 86%.

Figure 7 Father and son's educational achievements in urban aereas (in percent)

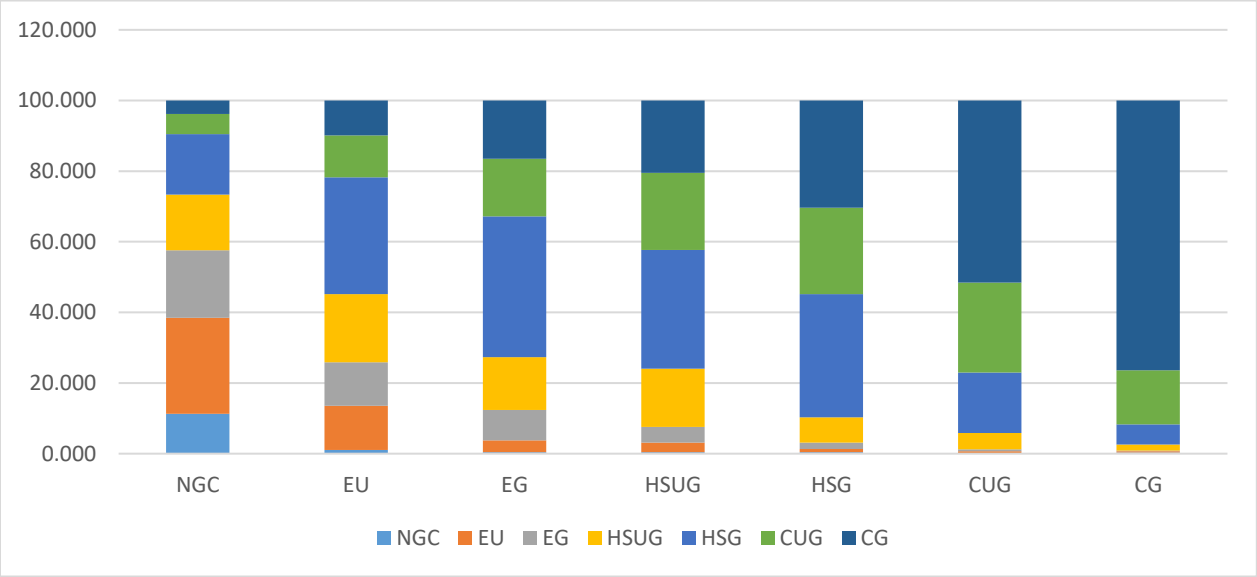


Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A2

4.1.4 Daughter's and fathers' educational achievements

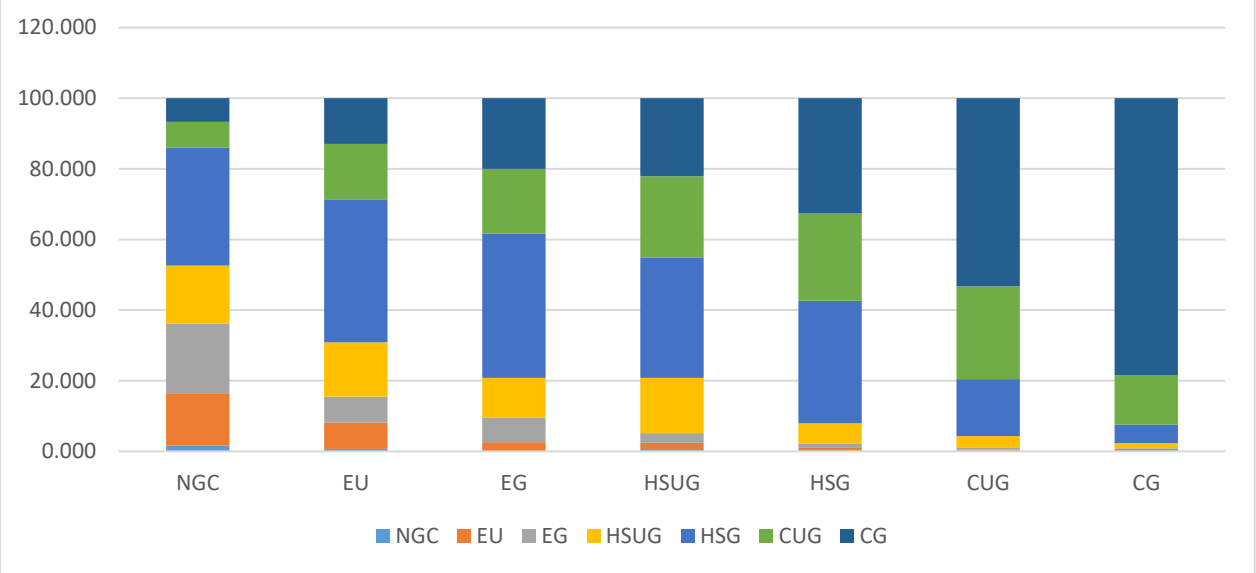
Daughters appear to maintain a high chance of graduating from college given that their fathers have done so. On average, 76% of college educated fathers have daughters who finish college. For fathers who have attended college, more than 50% of their daughters have finished college. Fathers in urban areas appear to have relatively higher proportions of daughters who finished college compared with their rural based counterparts.

Figure 8 Father and daughter's educational achievements: Both urban and rural (in percent)



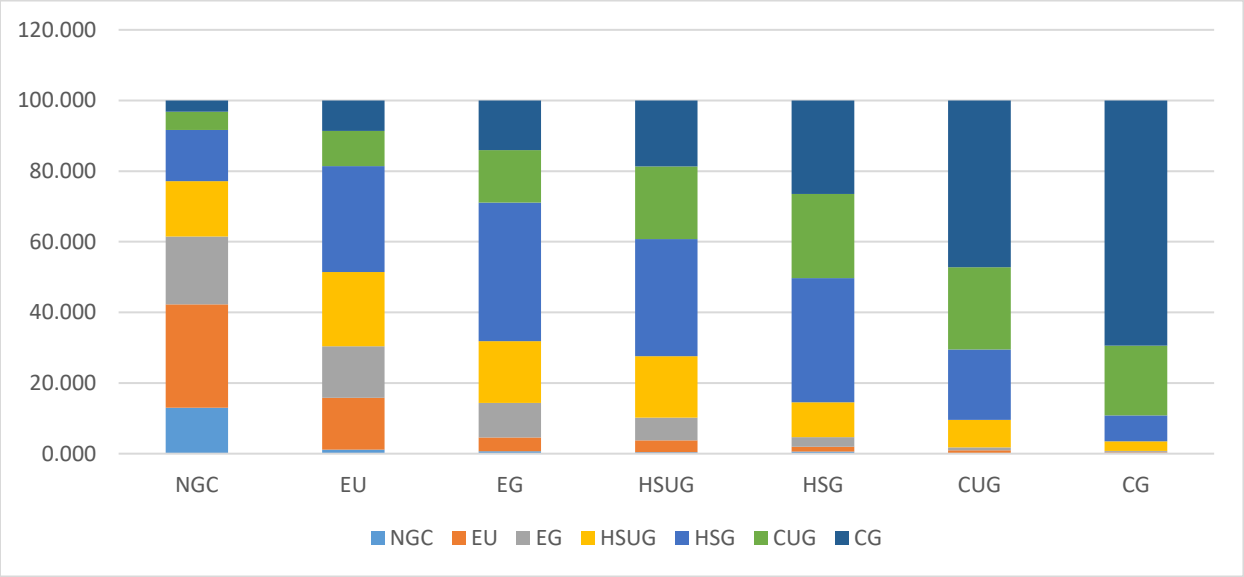
Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A2

Figure 9 Father and daughter's educational achievements: Urban (in percent)



Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A2

Figure 10 Father and daughter's educational achievements: Rural (in percent)

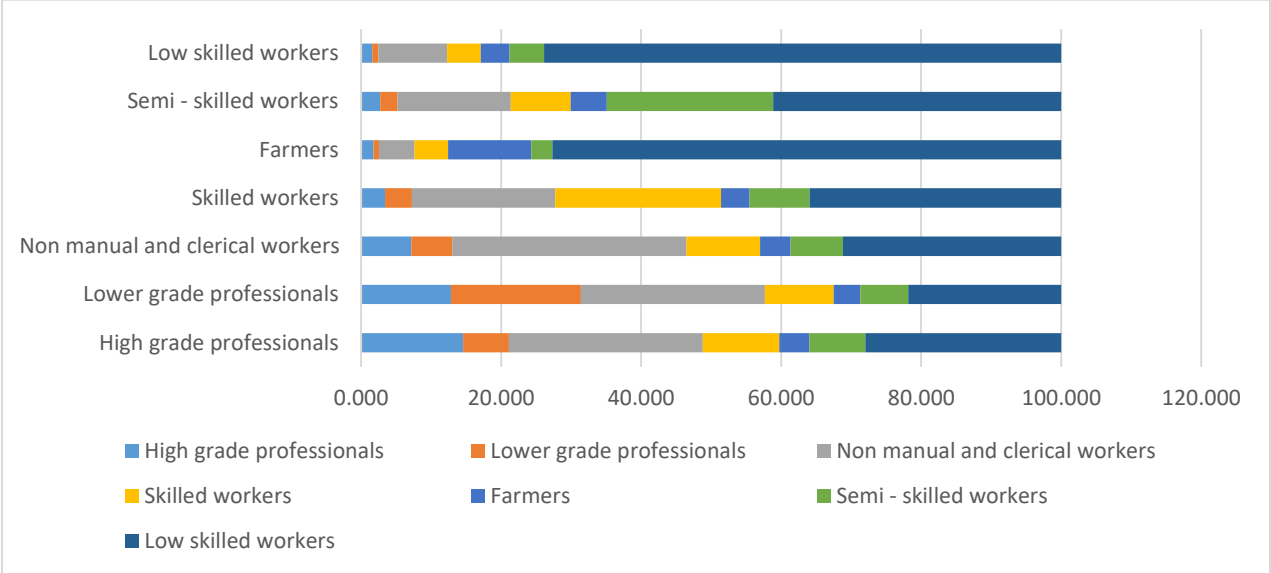


Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A2

4.1.5 Son and father's occupation

There appears to be low indication that the son's occupation will be highly correlated with the father's occupation. For instance, only 14% of fathers considered as high professionals have children classified under such. The match is quite high though for manual jobs, with low skilled jobs match topping more than 60%.

Figure 11 Father and son's occupation:Both urban and rural areas



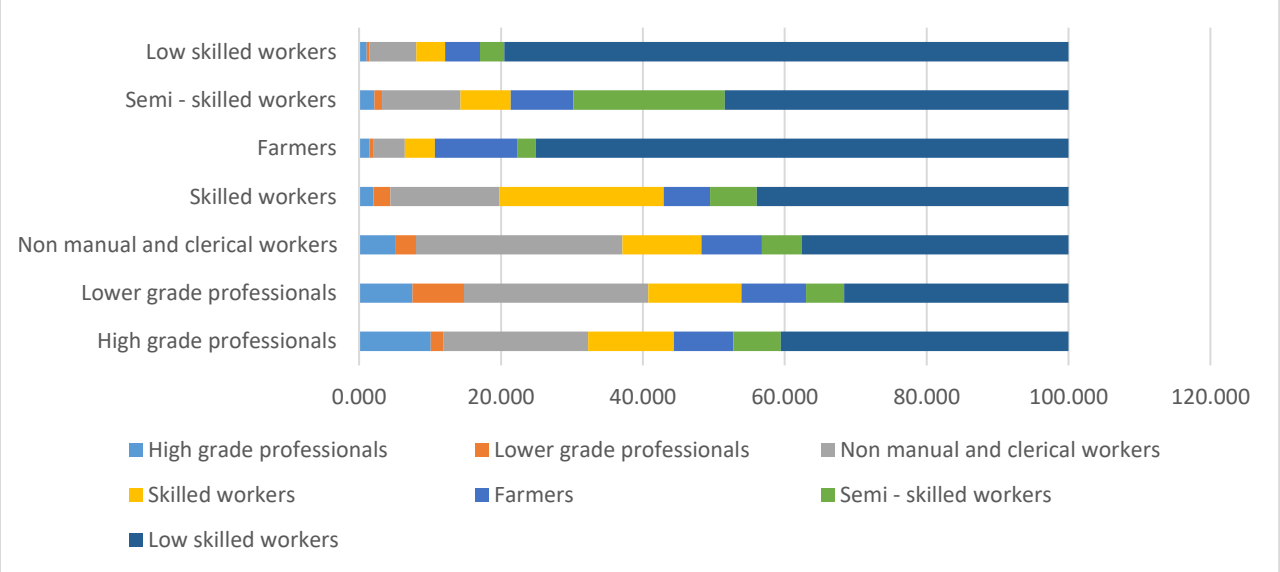
Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A5

When we look into the national average, it seems that even when fathers are classified as high professionals, sons have diverse occupational profiles. Close to 50% are classified as manual workers. In urban areas, the respective proportions associated with fathers whose occupations are the same as their sons, are higher than their rural based counterparts. Those whose fathers are lower professionals have better profiles for sons. The proportion of them landing on manual jobs is lower than their high professional counterparts.

Figure 12 Father and son's occupation: Urban areas

Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A5

Figure 13 Father and son's occupation: Rural areas



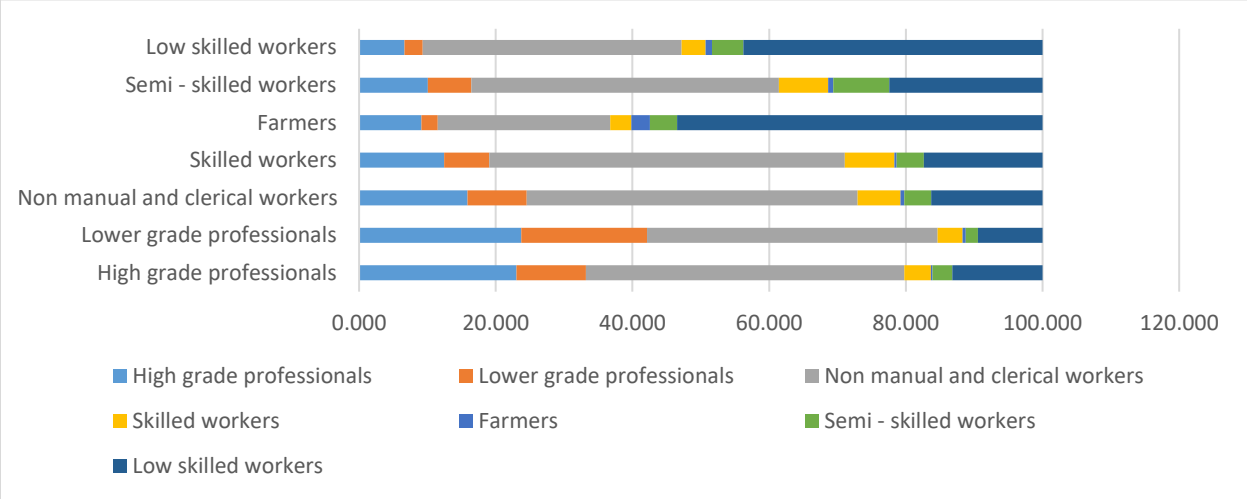
Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A5

4.1.6 Daughter's and fathers' occupation

In sharp contrast, the relationship between father and daughter in terms of occupation appears to support a better matched profile. For instance, fathers which are high professionals have daughters who are classified as belonging to high professionals, lower professionals and non – manual workers. Only 20% are in occupations considered manual.

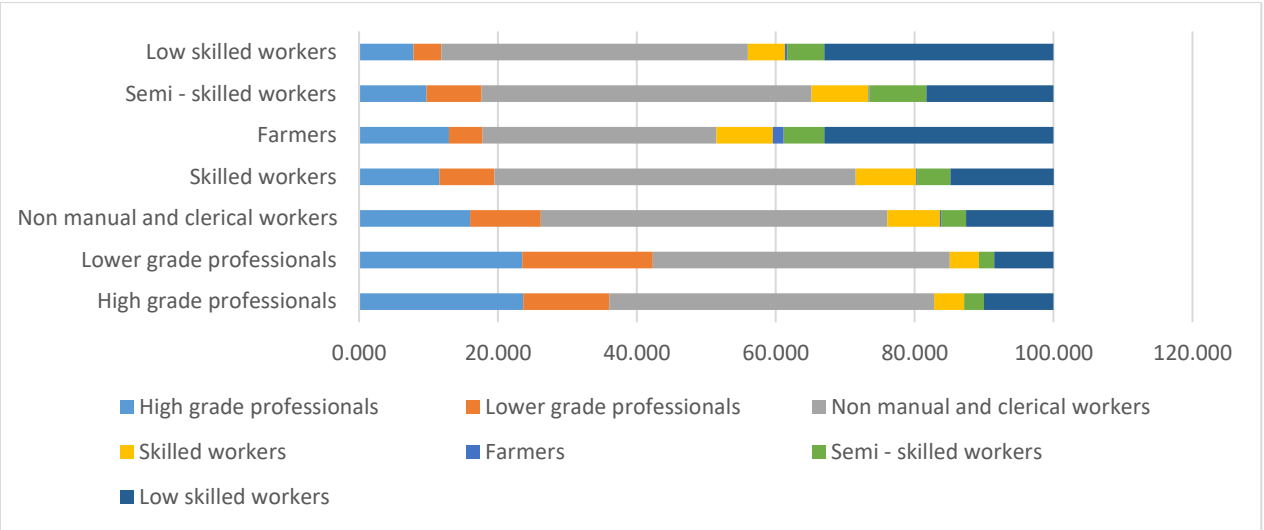
It is also noteworthy that daughters, regardless of fathers' occupation tend to become non – manual workers which is traditionally associated with female workers.

Figure 14 Father and daughter's occupation:Both urban and rural areas



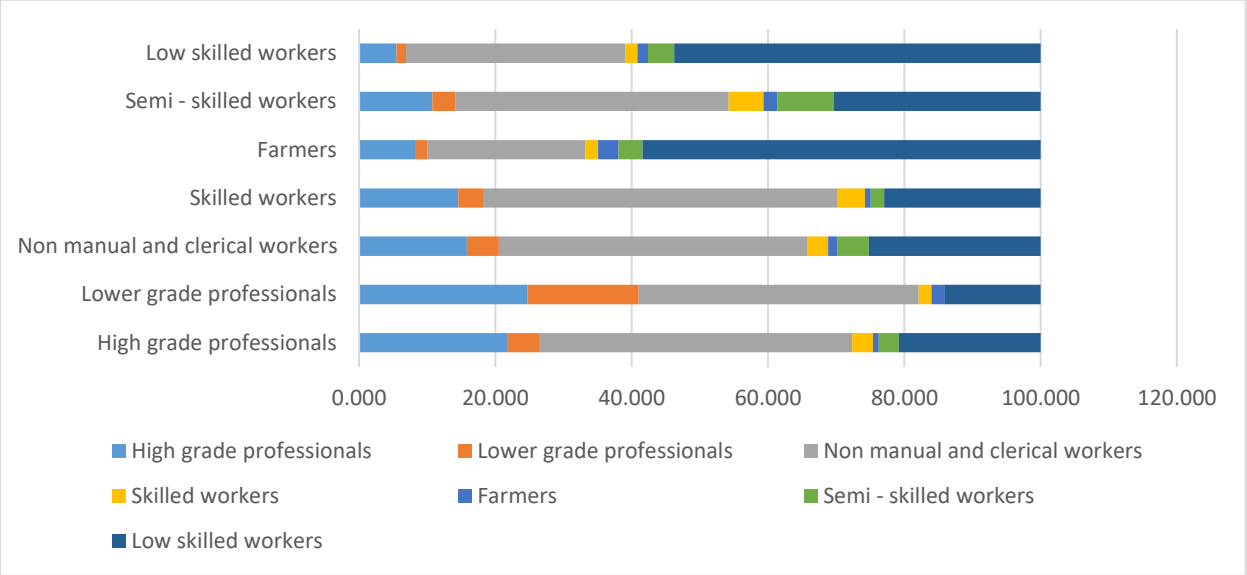
Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A5

Figure 15 Father and daughter's occupation: urban areas



Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A5

Figure 16 Father and daughter's occupation: rural areas



Note: figures pertain to proportions, averaged over a period of 7 years (2003 – 2009). All estimates are computed using October rounds of the Labor Force Survey (LFS). Actual estimates are also reported in Table A5

4.1.6 Impact of household composition

Based on the preceding information, we can have a fairly intuitive understanding of some stylized facts on father – children pairs. However, the estimates do not explicitly account for the statistical effects of the number of sons and daughters in the household. This means that we cannot distinguish the impact of having one son or daughter on educational achievements relative to a household with 2 sons or daughters. For us to paint a more micro picture, we report stylized facts on table A6. Note that due to sample reduction, we will no longer report households with more than 2 sons or daughters.

When we focused on households with one daughter or one son, it can be seen that the relative proportion of college graduates is greater relative to 2 son or 2 daughter households. While it has been established in the foregoing tables that a larger proportion of daughters graduate from college, table A6 shows that in households where there is 1 daughter or son, the proportion of daughters achieving college education is much higher compared with households with 1 son. Daughters also show considerable stability compared with sons at the top levels of education.

As far as father's occupation is concerned, there are more daughters who are professionals and skilled workers in 1 son or daughter households. The numbers do not change that much when we focus on households with 2 sons or 2 daughters.

4.2 Wage penalties and premia: parental education

Following CSJ, regressions are carried out separately for men and women. Wage regressions are specified the usual way. Control variables include age, age squared, permanent status, regional residence, marital status, urbanity, industrial affiliation and occupation.[38]

Using a series of cross – sections spanning 2003 to 2009, we first estimate measures of mobility and focus on wage persistence using father – son and then father – daughter pairs.

4.2.1 Son – father pairs: OLS

In regression models where only father's education is presumed to matter (denoted by S1), with results shown in Figure 17, wage gains are significantly higher for sons with college educated fathers. For instance, in 2002, the wage gains of sons shot up to more than 50% relative to the reference group. In sharp contrast, sons with low educated fathers suffered wage penalties amounting to more than 20% in the same year. The gap between the two groups was sustained until 2006 as it began to narrow the year after. There were two years (2008-2009) during which wage gains became negligible but wage losses continued to be quite significant. It is also noteworthy that the wage effects of one's own schooling is robustly positive even when gains are quite small. Except for 2004, it can be observed that returns are at least 10% higher than those in the reference category. It is surprising, though, that returns in 2009 have dipped below the zero line.

Figure 17 Wage gains and losses of sons

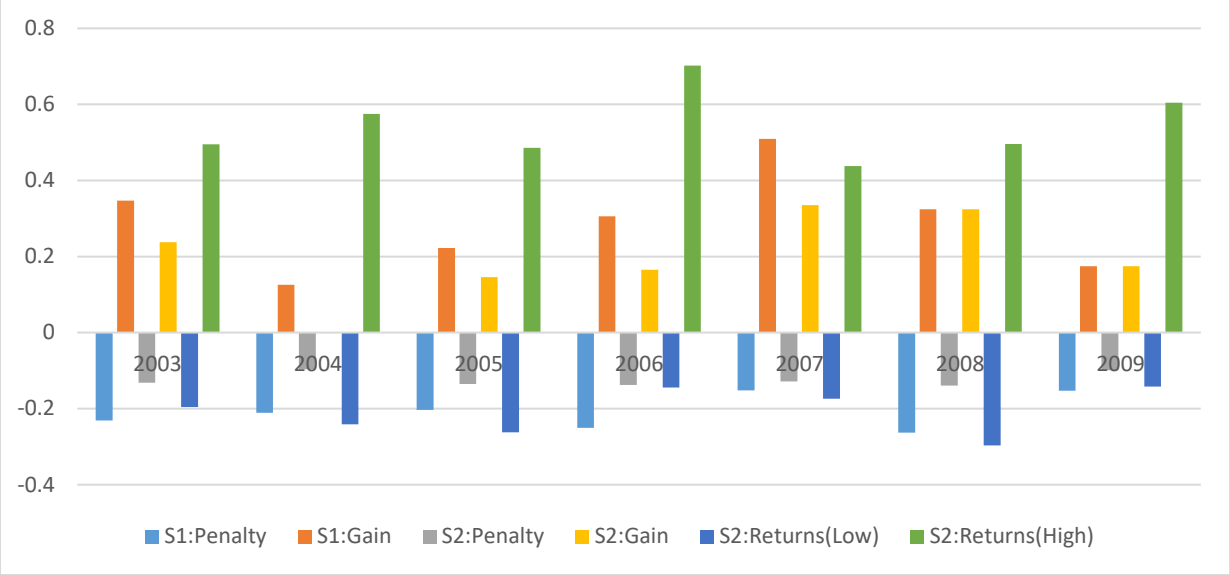
Note: S1 pertains to specifications that admits father's schooling achievements relative to high school graduate. S2 now includes the son's schooling achievements. Returns are those associated with the son's schooling achievements.

4.2.2 Daughter – Father pairs: OLS

[38] While it is observed that some workers report zero earnings, estimates are entirely based on respondents who report wages. Again, this results in significant reductions in sample size given that informal sector workers are more likely not to report earnings relative to those employed in the corporate and public sectors.

High education pays well for employed daughters. Without controlling for their own education, daughters with highly educated fathers tend to have high wage gains relative to moderately educated fathers.

Figure 18 Wage gains and losses of daughters



Note: S1 pertains to specifications that admits father's schooling achievements relative to high school graduate. S2 now includes the son's schooling achievements. Returns are those associated with the son's schooling achievements.

Their gains are as high as 40%. Wage losses of daughters with less educated fathers are also quite high. The main distinctions between sons and daughters are the following: (a) wage gains for daughters have not flat lined in 2009 and (b) returns to education for daughters are higher than sons. The latter implies that the wage gap between less and better educated daughters will be persistent.

4.3 Wage elasticity

4.3.1 Sample selection rules

At this point, we acknowledge that because of too much parameter uncertainty, we extend the scope of empirical investigation to accommodate various sample selection rules. Following Ng, Xhen, & Ho (2009), we need to pay close attention to how various sample selection rules determine differences among estimates and come up with a reasonable range of estimates. We will only focus on father – children pairs due to sample attrition encountered when dealing with mother – children pairs.[39]

For generating samples for sons and daughters we limit our sample to individuals belonging to the 15 to 64 age group. Being mindful of life – cycle bias, we experiment by using several age groups for sons or daughters. We will also be using permanent worker status.

[39] Initially, mother – daughter and son pairs were included but due to selection rules, sample sizes were no longer sufficient to yield feasible estimates.

Our samples do not admit individuals who work for the first time. While there is a reason to believe that female workers self – select in the labor market, we do not control for sample selection at this point.

In the LFS, basic gross daily pay is reported along with the basis of payment.[40] Wage rates are computed by dividing earnings by labor hours. In regression runs, observations with missing wage data will be automatically be removed.

We compare estimates for each year in the 2003 – 2009. First, we estimate the correlation between log wages of sons/daughters relative to fathers/mothers using OLS, augmented by the ratio of standard deviation of relative wages. Second, we use for the same sample containing both parental and children outcomes, the linear IV method, using as instruments, parental occupation and education.

Estimates are further conditioned using age restrictions for sons/daughters. Since we don't have access to career history which is critical for measuring lifetime earnings and the correlation its correlation with current earnings, we will also use permanent status in order to increase correlation with current and lifetime earnings. Based on the data statistics, there is serious sample attrition when we use a sample of non – permanent workers. Considerable bias is registered as some estimates breach 1 and have high standard errors.

4.3.2 Results

Tables A7 and A8 show the respective estimates based on different restrictions. Starting off, estimates based on the full sample confirm what the literature has been saying all along, that is, mobility estimates based on OLS suffer from attenuation bias for several known reasons. First, as mentioned, permanent income of fathers is not measured properly by using current wages. Second, there is attenuation bias because included sons or daughters in the sample may be too young in their life – cycle, predictably earning less during the early years of their careers. This may imply that using a variable that indicates permanent job status may yield benefits. Third, there is a possibility that the age and occupational status of fathers may cause attenuation. Fourth, there is also a possibility that urbanity may introduce wage disparities. Thus, including it may allow us to understand how geographical differences may determine the magnitude of the mobility estimate. Fifth, as sample size decreases significantly due to sample selection rules, there may be too much downward bias which may overstate mobility gains.

Based on Tables A7 and A8, we can observe that OLS estimates are, in general, lower than their IV estimates. This is because factors like father's occupation and education have a positive way of affecting wages of sons. Here are some empirical observations:

Role of restrictions. Without imposing restrictions, there is no doubt that full sample – based mobility estimates may be underestimated as they include younger sons or daughters. This may convey the false impression that wage mobility is high. Restrictions play a role in countering this result. A simple selection rule restricting age of sons or daughters to 25 to 35 age group conforms with the predictable general effect of increasing the coefficient estimate,

[40] Earnings from other jobs were not included due to the prevalence of missing values.

thereby indicating relatively lower mobility. Evidence is not consistent throughout the entire period, though.

Job status. We recognize that wage data may be dominated by transitory effects, either emanating from the macroeconomy or labor market. While it may serve as an imperfect indicator of wage or earnings stability, job status may be important to assess mobility patterns. It is important, though, not to overlook that job status alone will not connote that differences between permanent and current earnings have been minimized. The logic behind this is simple. Because no information on job history or career is given, we can use job status. It turns out that father's permanent status may be associated with higher mobility. Relative immobility is generally observed for son's whose job status is not permanent. (OLS3 & IV3) For daughters, having a father with permanent job status is associated with higher mobility, replicating the empirical evidence for sons.

Data realities. We set out to determine whether empirical feasibility can be one of the properties of survey data on labor market outcomes. The answer is that feasibility is not an even characterization of subsamples associated across restrictions. As expected, intricacies abound. The effect of sample selection rules is to reduce the samples, leading to surprisingly low estimates, thereby conveying falsely, high mobility. Surprisingly, there are mobility estimates that are comparable across estimation platforms. This implies that instruments are not strong enough or do not significantly raise the wages of sons. Thus, we can say that mobility studies really require a large number of data points to permit occupation profiles to differ across urban and rural areas. Results also show that regardless of urbanity, sons whose fathers' job status is non – permanent appear to be less mobile than their counterparts with fathers whose job status is permanent. Urban based fathers appear to have higher coefficient estimates for IV compared with their rural counterparts.

Econometric irregularities I. In theory, as long as instruments are positively correlated with child wage outcomes, the impact of father's instrumented permanent income should be higher compared with non – treated current income. As one of the irregularities, there are instances wherein IV based estimates are even lower than OLS based ones. When interpreted, it means that father's occupation and education may even work against the child's performance in the labor market. This instance of reversal is not commonly observed in the literature and it may be an artifact of bias.

Econometric irregularities II. Data on father – daughter pairs appear to suffer greater biases than their son counterparts. The primary suspect is the sample size. Biases may come in the form of self – selection bias which occurs when the latent factors that drive decisions to participate in the labor form are correlated with unknown factors that drive higher wages

Age restrictions and life cycle bias. With the age restriction, daughters appear to be less mobile than sons. Linking this up with some strong relationships in terms of occupational choices between them and their fathers and educational achievement, the higher estimates. having a sample with older children and fathers result in higher measured mobility for OLS but offset when father's attributes are used to instrument permanent income.

Mobility relative to father's median wage. Following Ferreira & Veloso (2006), we divide the sample into two using the median of the father's wage as reference. Table A10 shows a

pattern for daughters. Regardless of location relative to father's median wage, daughters are invariably less mobile compared with their male counterparts. This reflects the evidence shown by the transition matrices. Evidence also show that daughters whose father's wage is above the median are more mobile relative to those whose father's wage falls below it.

Island – based mobility. Based on estimates shown in table A9, Luzon – based households are relatively more mobile, followed by those in NCR and Visayas. The biggest surprise is those from Mindanao, indicating that the degree of persistence is the weakest among all islands.

4.4. Wage distributions and transition matrix

After evaluating the feasibility of using data pairs to estimate elasticities, we now turn our attention to the estimation of transition matrices involving wage quintiles by sons, daughters and their parents. The limitations of using wage data apply and we do not attempt at this point to facilitate temporal comparisons.

Ascertaining distributional properties is critical to understanding mobility. Elasticity estimates are point estimates which means that we only see a measure associated with the conditional wage distribution. A more useful statistic which is generated from ordered probit estimates pertain to probabilities in the transition matrix. Notwithstanding the limitations posed by the lack of panel data, this allows us to answer questions about distributional features of mobility.

Probabilities are presented in the tables A11 and A12. Because parental investments may vary depending on the composition of households, we included results based on the number of sons or daughters. Because of the loss in sample points as a result of focusing on specific number of sons or daughters, we only focused on households with up to 2 sons or daughters.

Using father's wage distribution as preference, what tables A11 and A12 remind us is that there is tremendous persistence at the bottom and top especially for sons. For daughters, there is less at the bottom 20% but highly persistent at the top, nonetheless. In households where there is only 1 son, persistence at the bottom decreases but it becomes even more pronounced at the top. When the number of sons increases to 2, persistence at the bottom becomes stronger but a reduction at the top is observed.

Results for sons and daughters using mother's wage distribution appear to replicated those based on fathers'.

4.5 Parental education and children's education: Probability estimates

We now proceed to estimating parental education effects on child's education outcomes. This supplements the elasticity analysis but stands to offer much richer empirical outcomes as it contains information accounting for differences among households in terms of location, ability to generate nonlabor income such as remittances and other controls.

By interpreting educational attainment as the result of a nonlinear data generating process, we are able to frame more questions on how parental education can influence child education outcomes. Using STATA, we were able to compute for various probabilities associated with

the educational attainment of the child. First, using external information, we compute the probabilities associated with specific profiles. This will answer the following question: what is the probability that a child will finish college given that both parents have both finished secondary education and the household resides in a relatively poor region with average values of remittances and household composition variables? Second we estimate the probability of each outcome based on groups samples belong to. For instance, what is the probability that the child will end up finishing college if he comes from households with college educated fathers? More interestingly, we need to quantify the likelihood that children from poor households will graduate from college. Third, we generate results pertaining to covariate effects on individual probabilities, contrasting the relative impact of parental education. This answers the question on how a change from a reference education achievement to other levels would affect the outcome.

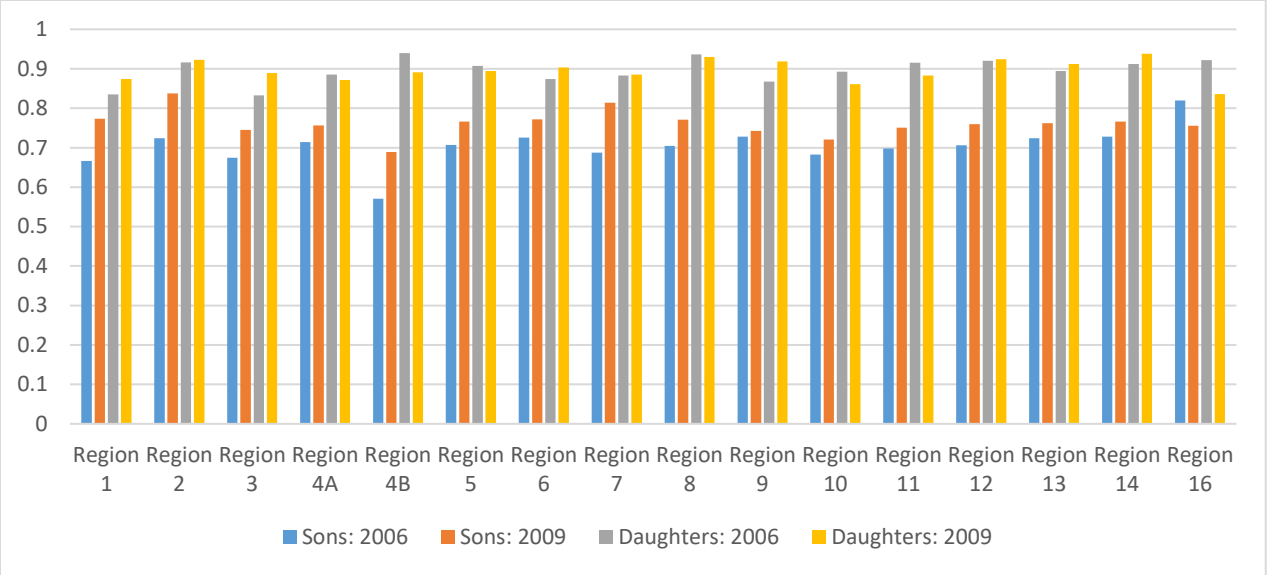
4.5.1 College educated parents vs their high school graduate counterparts

Data show that there are significant number of parents with identical educational achievements. Without dismissing the value of undergraduates, we only focus on two parental educational outcomes (high school graduates and college graduates) and evaluate regional disparities in terms of probability estimates. Thus, the analysis proceeds from the assumption that other key variables are measured at their respective means, implying that the only change comes from location.

The exercise relies strongly on the assumption that parameters are structural in the sense that family structures are homogeneous across regions, which may not be plausible considering fertility profiles may vary location – wise. Of course, this kind of analysis does not incorporate the quality of school attended, the course obtained by college educated parents, and other key variables that determine child's education outcomes such as school resources, learning experiences, direct and indirect costs associated with education, among others.

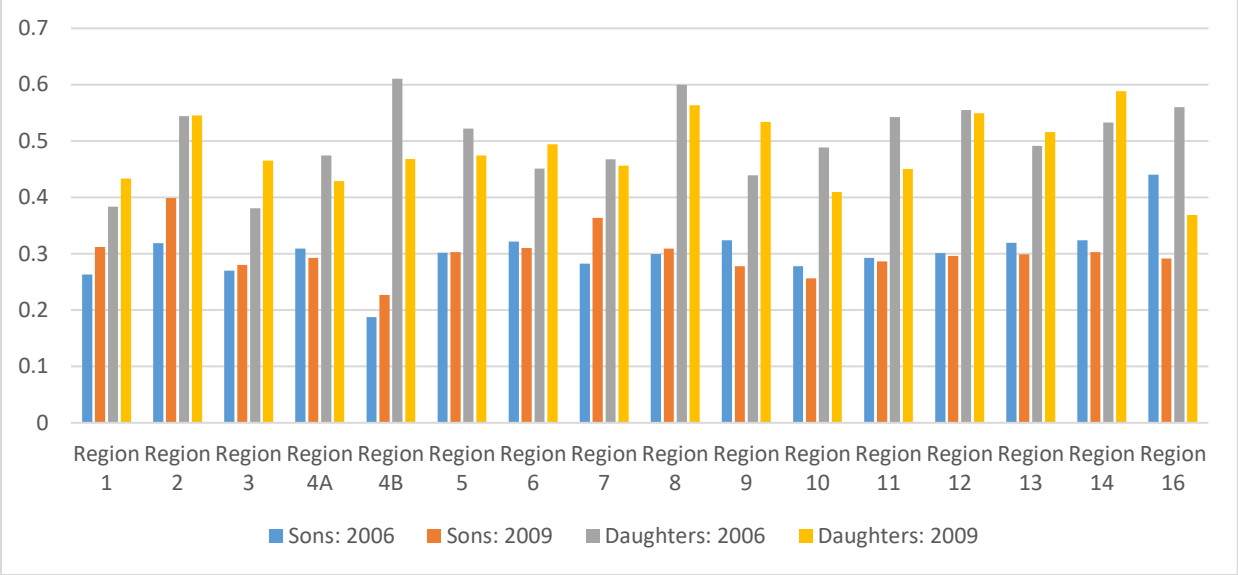
Results for this exercise are found in Figures 19 – 22. Assuming that households receive the same amount of remittances (mean remittances), daughters whose parents are both college educated have higher chance of finishing college relative to sons, regardless of urbanity and region of residence. The same is true if both parents finished high school only. This appears to bolster preliminary statistical evidence showing that daughters are more likely to match their father's education compared with sons. Given parameter estimates, there is an appreciable increase in the probability that sons will finish college in 2009 compared with 2006. Sons are more likely to end up as college undergraduates than daughters regardless of urbanity and region of residence.

Figure 19 Estimated probabilities that a son or daughter will finish college in 2006 and 2009: College Educated parents in urban ares



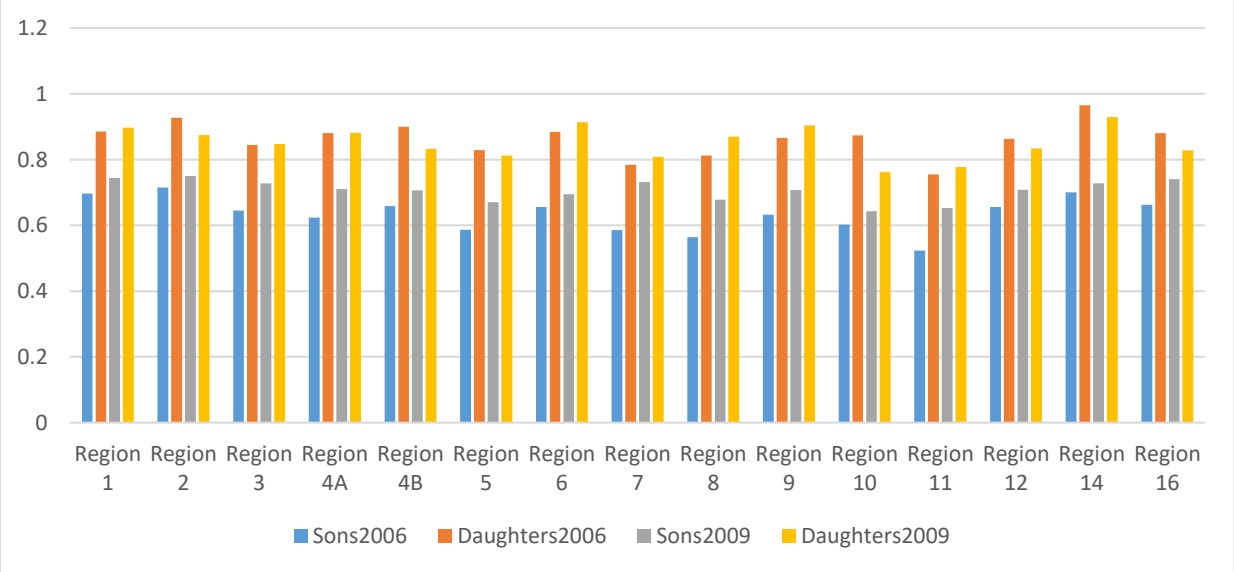
Note: probabilities were predicted by pegging the educational achievements of both parents to college graduate and evaluating the rest of the included regressors at their respective mean values. To get the region – specific probability, one needs to evaluate the estimated model by setting the region dummy of interest to 1 and 0 otherwise.

Figure 20 Estimated probabilities that a son or daughter will finish college in 2006 and 2009: College Educated parents in rural areas



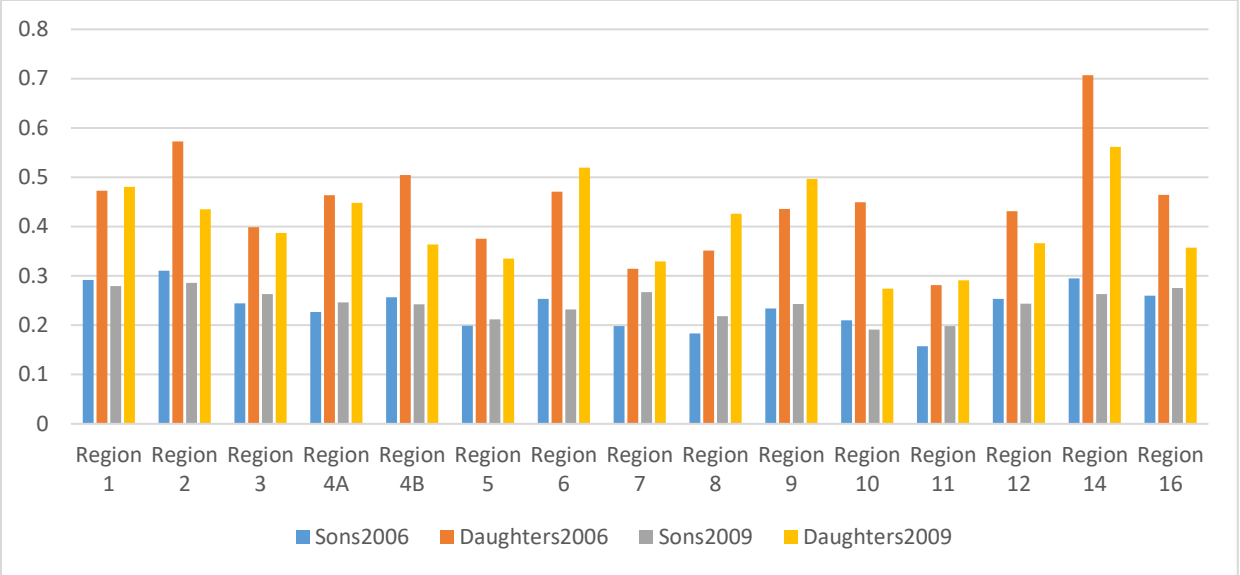
Note: probabilities were predicted by pegging the educational achievements of both parents to college graduate and evaluating the rest of the included regressors at their respective mean values. To get the region – specific probability, one needs to evaluate the estimated model by setting the region dummy of interest to 1 and 0 otherwise.

Figure 21Estimated probabilities that a son or daughter will finish college in 2006 and 2009: Both parents are high school graduates and reside in urban areas



Note: probabilities were predicted by pegging the educational achievements of both parents to high school graduate and evaluating the rest of the included regressors at their respective mean values. To get the region – specific probability, one needs to evaluate the estimated model by setting the region dummy of interest to 1 and 0 otherwise.

Figure 22 Estimated probabilities that a son or daughter will finish college in 2006 and 2009: Both parents are high school graduates and reside in rural areas



Note: probabilities were predicted by pegging the educational achievements of both parents to high school graduate and evaluating the rest of the included regressors at their respective mean values. To get the region – specific probability, one needs to evaluate the estimated model by setting the region dummy of interest to 1 and 0 otherwise.

4.5.2 Group – specific probabilities

Suppose we are interested in determining group – specific differences in terms of the educational achievements of sons and daughters. Will the probability associated with such outcomes be the same between two groups, say among fathers and mothers?

As shown in tables A13 and A14, estimates indicate that the probability of sons getting college degrees relative to their fathers and mothers have increased from 2006 to 2009. Conversely, the probability of daughters graduating from college relative to their fathers and mothers have decreased slightly for the same period. The probability that daughters will finish college in households with college educated fathers and mothers is higher compared with sons. Even for low levels of parental education, there is an appreciable difference in achievement probabilities between daughters and sons.

The most interesting result concerns the disparities between poor and nonpoor households in terms of the probability that a son or daughter will finish college. Among nonpoor households, the probability that a daughter will graduate from college is 42% compared with 23.6% for poor households in 2006. For sons, the probability is 20.7% compared with 10.3%. This confirms what we knew all along, that is, poorer households may be less able to send their children to college and there is a relative disparity between sons and daughters in terms of educational attainment.

4.5.3 Marginal effects

It is also instructive to examine marginal effects on various outcomes. Of particular interest is the marginal effect of contributions from abroad or remittances as it may yield positive effects on the probability that a son or daughter may be able to finish a higher level of schooling. Again, we are operating on the assumption that due to the heterogeneity of

households as well as educational references, remittance effects are not uniformly distributed.

Based on stylized facts shown in tables A15 and A16, it is clear that even when parents' educational attainment is below college, there is nonzero chance that the daughter or son will still graduate from college. However, this does not mean that the effects of educational attainment are going to be uniform across levels. For instance, when the outcome is high school graduate and the household values a college degree, the marginal effect of parental education is going to be negative.

There is evidence that the marginal effects of having college educated parents across sons and daughter are quantitatively different. Results support the empirical observation that mother's college education is an important factor in determining the schooling success of daughters.

There is also evidence that the marginal effects of mother's college education on sons has declined from 2006 to 2009. On the other hand, the marginal effects of father's college education have increased from 2006 to 2009. This is consistent with the earlier exercise predicting probabilities for a given set of attributes.

As shown by the positive values of urbanity's marginal effects, daughters are more likely to achieve college education if the household they belong to resides in urban areas. In contrast the estimated marginal effects for urbanity among sons is consistently negative for both years.

While significant as one of the determinants of the educational achievements, remittances have negative marginal effects on all outcomes except college education. This may be treated as an evidence favoring the notion that households believe in the strategic value of education in uplifting their sons/daughter's socio economic status.

To complete the picture, we also estimated the role of poverty, the marginal effect of poverty status in 2006 and 2009 is more negative for daughters than sons that they will finish college. This implies that when the household becomes worst off by becoming poor, daughters are less likely to graduate from college in 2006 compared with sons.

4.6 Evidence from selectivity (2006 and 2009)

The previous empirical exercise shows that it's important to account for parental education in characterizing educational achievement of sons and daughters. The exercise skirts data problems associated with the use of wages and highlights the extent of intergenerational education persistence. However, as recognized in the literature, sample selectivity concerns need to be addressed given that participation decisions of Filipino workers are non – random and have been found to be low among female workers. As an empirical matter, it is still instructive to provide evidence using Heckman's sample selection model for male (sons) and female (daughters) workers. The model provides us with a way to characterize the nature of selection. Relative to sons, do females, whose latent potential to receive higher wages correlate well with factors that determine employment decisions? Second, within the context of non – random decisions, we can reexamine the behavior of wages.

Results show that regardless of gender, workers are generally, negatively selected. Looking at the elasticity estimates found in tables A18 and A19, it is clear that daughters have higher persistence than sons for both years. However, while the gap was quite large in 2006, estimates for 2009 show a huge reduction in persistence among daughters. Consistent with previous elasticity estimates, instrumented father's wages are also associated with persistence.

Selection problems are present in both son and daughter samples. This is deemed consistent with findings in the literature. However, selection problems for sons have become more evident in 2009. There are some significant findings. When only son or daughter's own education is used in the outcome equation, daughters are positively selected in both years, with the IMR becoming statistically significant in 2009. On average, those who have positively self – selected in 2009 earned more than 29% compared with a randomly selected woman from a population with similar average characteristics. For sons, there was positively selection in 2006 but selection was no longer significant in 2009. Estimated values allow us to infer that when own educational attainment is used, sons who positively selected in 2006 earned 36% higher compared with their counterparts drawn from the same population.

Positive selection which was induced by using one's own education was reversed in successive runs when parental information was incorporated. For daughters, the coefficients of the IMR for models that use father's raw and corrected wages have become more negative. The negativity implies that wages have shifted downward, as those who self – selected have average characteristics that are inferior compared to a randomly drawn observation. When parental education is used, the truncation effect (product of average IMR and the coefficient estimate of IMR) on daughters who selected into wage employment have become less negative in 2009 relative to 2006. In contrast, the truncation effect on sons has become more negative in 2009 relative to 2006. This means that sons who sought wage employment in 2009 are more worst – off relative to a randomly drawn male worker.

To summarize, we have observed that selection patterns for daughters are quite different from sons. Results show that the truncation effect responds negatively to the inclusion of parental educational achievements. This result sets apart selection models that control for parental influence on children's wage from model variants that do not, thereby highlighting mechanisms that may be proximate determinants of selection. While only cross – sectional data were used, it can be seen that higher persistence may be associated with the degree of truncation, with more negative truncation being plausibly associated with lower mobility.

5. Discussion

Despite the absence of long panels, this paper applies familiar methodologies using available cross – sectional data to empirically characterize mobility in the Philippine labor market. Offering partial characterization, the analytical platforms rely on wages and its permanent income proxy, educational attainment, as the primary economic status variables to facilitate intergenerational comparisons. As demonstrated, the quest to identify the appropriate bounds for mobility estimates has been difficult throughout the period 2003 – 2009, given the sensitivity of samples to a battery of sample selection rules and the lingering presence of difficult hurdles associated with the measurement of permanent income. Indeed, biases are

really hard to pin down and mitigate without benefiting from panel data. The resultant father – children data pairs appear to consist primarily of households with relatively young children and fathers with permanent job status residing in urban areas. Samples derived from households residing in rural areas with non – permanent fathers yielded estimates that were no longer feasible and credible. As a result of smaller sample sizes, biases associated with parent – daughter pairs are somewhat more severe.

Understandably, mobility – based empirical strategies that attempt to provide a complete characterization of labor market dynamics may be limited by two important considerations. First, the methodology prescribes that we only focus on pairs of working parents and children, with the condition that earnings data are complete. As normally done in other studies, the exclusion of some sample pairs on the basis of incomplete information may systematically bias results due to the non – random nature of decisions like co – residency (children still residing with their parents) and labor market participation. For instance, studies in the US point out the bias associated with the non – inclusion of fathers whose employment status were affected by recessions (see Drewianka & Mercan). In most instances, however, unemployed fathers or sons are automatically excluded from the estimation sample since they exacerbate the attenuation bias that usually characterize estimates. This effectively raises issues concerning selection, particularly those associated with women, whose wages may dip as a result of child – bearing and other causes of work intermittency. It also limits plausible inference that can be derived from the relationship between labor force participation and employment decisions and mobility. Second, analysis continue to rely on a set of limited covariates that have defined the empirical relationship, thereby leading to omissions. Variables like family structure and dynamics, labor market trends and institutions, and regional economic structures may be important in determining employment prospects. Despite these concerns, the empirical results based on such data pairs paint a picture consistent with stylized facts. As shown, women (daughters) in the labor market are more educated and appear to exhibit a high degree of occupational persistence relative to their fathers. While this is expected of daughters belonging to richer households, it also implies that when their fathers are situated below the median wage, the likelihood is high that their fortunes will not be as favorable. Given estimated transition matrices, we have fairly affirmed, up to a degree of confidence, that persistence is present among low and high earning households.

Early on, there is ample recognition and realization that in the absence of panel data, uncovering patterns need to be prioritized. These are patterns that are based on the degree of sensitivity of mobility estimates to variations in selection rules. Two important labor market indicators, namely, job and occupational status present critical information through which, we can understand unique and salient aspects of Philippine labor market, as far as mobility is concerned. While no historically complete set of information is available detailing labor market experiences, job status of parents, who with their average age, are considered as prime - age workers, may help ameliorate the degree of life – cycle biases. Applying the same logic, we may derive better estimates when we admit into the sample, sons or daughter with permanent work status. Thus, restricting the sample further yields an elasticity measures that averaged 0.506 for sons and 0.653 for daughters. Compared with estimates in the literature, the figures indicate relative immobility on the part of Filipino sons and

daughters. However, daughter's relative immobility is more evident compared with sons. Relative to fathers, there is evidence that occupational status is more persistent among daughters than sons. This persistence is reflected by elasticity estimates using the father's median wage as reference. It may be possible that daughters who come from relatively richer households are positively selected and secure high paying employment. Returns to schooling of daughters with highly educated fathers are robustly high compared with those with less educated fathers. On the other hand, another interpretation is that daughters of poorly educated fathers may find themselves situated in the lower end of the wage distribution. To demonstrate robustness, several models using samples on households with complete information on parents and offspring were estimated and results offered validation that daughters have indeed enjoyed higher likelihood of finishing a college degree.

Empirical remedies that provide alternatives to Mincerian wage functions exist. Following the Markovian nature of methodologies measuring intergenerational educational elasticities, we fit a nonlinear model variant to estimate the probability that a child will finish a particular level of schooling given parental education, a proxy for household resources and poverty status. Based on Table A17, persistence in intergenerational education outcomes is notable. While poverty status is patently endogenous, the results highlight disparities in educational outcomes between poor and non – poor households. Regardless of gender, children from non – poor households achieve better educational outcomes. Evidence showing significant effects from parental education is indicative of the degree of advantage of children living in households with highly educated parents.

The implications for children from poor households are obvious. First, because their parents' educational profiles are relatively inferior, they stand to face wage penalties and low education returns (see Figures 17 & 18). Second, financial constraints may adversely limit the household's ability to defray direct and indirect costs of education, thereby limiting them to relatively low levels of education. This may potentially result in high intergenerational education persistence. Third, while not present in the data, the higher influence of maternal education may simply highlight the degree of involvement of mothers during the child's early formative years. Thus, it can be plausibly inferred that differences in quality of parental inputs may exist between poor and nonpoor households and this may eventually translate into permanent differences skills valued in the labor market.

The observed high degree of persistence can be used to shed light on how disparities in labor market performance would affect the mobility of workers. One important benefit derived from all the exercises is that they provide benchmarks of what to expect if labor market mechanisms of reward and penalties do not change, that is, if models chosen to act as empirical anchors yield estimates on schooling returns and selection patterns that are structural. It has been documented in this study, as in elsewhere, that Filipino women attain higher levels of education compared with their male counterparts. As shown in the results, daughters also have a higher degree of occupational persistence in jobs that are of high skill content (professionals and non – manual workers). Unfortunately, there is also a kind of persistence that is associated with the occupation of low skilled fathers. A large proportion of sons continue to linger in manual and elementary occupations. Even after altering the design and introducing LFS – FIES samples of households with both sons and daughters at

the same time, daughters still appeared to be more persistent in 2009 than they were in 2006. For sons, the situation across the two years have been comparable.

We now relate our results to some external findings. There is a World Bank study (Luo, 2009) that focuses on the labor market, fortunately covering most of the years included in the sample period. In the said paper, it was found that regional disparities in the labor market exist and that women along with the youth and those with less education face more challenges in getting employed or earning a good salary. Disparities may be traced to regional differences in industrial structure and human capital endowment. Using Oaxaca – based decompositions, it was shown that earnings differences attributable to regional structural characteristics are more important than differences based on individual characteristics in explaining variations in employment and earnings. Consistent with the literature, it was also reported that education provides a better chance for getting jobs and earning high salaries and that the gender wage differential is small.

Apparently, questions that pertain to such cannot be adequately answered by mobility analyses. The more serious finding is that real daily earnings over the period 2003 – 2007 has declined. Expectedly, this has tremendous effect on participation of the youth as well as on mobility if investments in children's education suffer as a result of low earnings. Thus, children may be further relegated into the lower part of their generation's earnings distribution due to low schooling returns. Youth unemployment may be addressed through minimum wage policy. However, an offshoot may be to encourage the youth to stay in school and improve knowledge and upgrade skill sets.

To supplement our discussion of mobility in light of labor market developments, we also appeal to stylized facts based on full samples derived from various LFS rounds. The Philippine Statistics Authority's (PSA) labor market reports for the years 2003 to 2009 reveal features of the labor market. As summarized in Table B1, the primary driver of employment has been the service sector, with the subsector real estate, renting and business services registering robust growth. From 2002 to 2009, the number of employed persons in this sector almost doubled, from 544,000 to 1. 066 million in 2009. For the same period, the subsectors hotels and restaurants, transport and financial intermediaries grew by 45%, 23.9% and 18.6%, respectively. In contrast, the respective employment growth rates between 2002 and 2009 in agriculture and industry were 8.28% and 8.4%.

Clearly, agriculture and industry have been sluggish in terms of employment growth. Table B1 has some serious implications for policy. Policy makers need to anticipate growth areas and identify the necessary skill sets for workers to be productive. This is something that is being done but careful emphasis should be made in terms of its importance in increasing mobility. Forecasting labor market demand is clearly an important undertaking.

Furthermore, we can determine the composition of industries by looking into the relative proportions of male and female workers by educational attainment and occupation. Based on Table B2, it is clear that the relative proportion of women who attained high levels of schooling is high in sectors like wholesale and retail trade, finance, hotels and restaurants, public services and private households. As shown in Table B3, the relative proportions of women as professionals and non – manual workers are high in wholesale and retail trade,

hotels and restaurants, the financial sector, and public services. Low and semi-skilled male workers are found in almost all sectors except wholesale and retail trade and private households. Undoubtedly manual skilled jobs are dominated by men.

In terms of full – time employment, the 2003 BLES report indicates a robust growth. However, in 2009, a rise in part – time employment has been registered, with full time employment showing a decline. If this becomes a trend, it may be translated in terms of lower mobility since part – time employment tends to offer inferior benefits compared with full time employment. High turnover rates that characterize part time or contractual employment mean limited opportunities for training and other skill – related activities. The distribution of jobs across industries appear to be uneven at best, as the respective proportions of relatively less skilled workers become evident. As shown in Tables B4 and B5, small proportions of male and female workers are classified as professionals and non – manual workers, except in hotels and restaurants, the financial sector, business services, public services, and international organizations.

Underemployment remains a significant problem. Based on computed statistics, the average underemployment rate for 2003 – 2009 reached 18%. The underemployment rates for 2008 and 2009 stood at more than 19.1 and 19.3, respectively, implying that 1 in every 5 employed workers yearn for additional working hours to augment daily income. As shown in table B6, there are two problematic sectors that generate high rates of underemployment for both male and female workers, namely the agricultural and retail trade sectors. Male agricultural workers account for almost 40% of underemployed workers. Workers categorized as farmers and unskilled workers account for a staggering 98% of all underemployed male workers in the agricultural sector. Other sectors like construction and transportation also registered high underemployment rates given the nature of jobs in the two sectors. For females, private households, retail trade yield high rates of underemployment.

As already known, unemployment leads to fall in earnings which may lead to low mobility. The unemployment rate between 2008 and 2009 remained relatively unchanged at 7.4. and 7.5, respectively. Youth unemployment remains persistent. Those from the 15 to 24 age group continued to experience high unemployment rates. The probability of males being unemployed is higher than females. This is also evident across regions as shown in Table B10. Education plays a key role in securing employment, as majority of the unemployed have finished no more than high school. As expected, college graduates tend to have lower unemployment rates, confirming once again that it is important to invest in education.

Over a period of 7 years, labor force participation rates of male and female workers have diverged sharply with the latter's participation rate falling below 40%. Based on Table B7, disparities between male and female workers are evident. For the 15 – 24 age group, the proportion of females considered not a part of the labor force is about 65%, more than 20 percentage points higher than male workers. For the 25 – 54 age group, the results are even more staggering. Women who don't participate in the labor market are 8 times higher than men. While we observe that the proportion of men not participating in the labor force start to climb past the age of 54, they are still more than 20 percentage points lower than women.

We now relate the education profile of labor force participants. Tables B7, B8, B9, and B10 confirm three largely known facts. First, women have relatively lower unemployment rates than men. This is also true across regional residence. Second, regardless of educational attainment, the proportion of women who do not participate in the labor force alarmingly exceeds those of men and even the national average. This is also robust across regional residence. Third, women who finish college do not tend to participate in the labor force, registering a modest proportion for those employed. Fourth, those with lower levels of schooling tend to participate actively in the labor force.

At the heart of labor force participation decisions is the concept of selectivity. It is known that marital status plays a significant role in women's labor force participation decisions. Table B9 may determine whether married or single, men tend to have high participation rates compared with women. Of course, this can be attributable to traditional roles of women. Highly educated workers who have abilities that merit high expected wages and factors that increase propensity to join the labor market may be more mobile than their parents. However, it may also be the case that workers negatively self – select, thereby affecting the wage offers that they can realized. In this case, their relative mobility may be lower than those who positively select. A negative selection means that workers' characteristics that push them to seek employment may not work well in the labor market, thereby resulting in lower wages. As shown in tables A18 and A19, one of the critical differences between sons and daughters is the sign of the inverse mills ratio. Using the son or daughter's own educational attainment, daughters are positively selected in 2006 and 2009. On the other hand, results pertaining to sons show the opposite. Because it's the worker's educational attainment that may be more informative to employers, we can argue that negative selection is more associated with higher persistence or limited mobility. Instrumenting for father's permanent income, mobility is lower for both sons and daughters but more pronounced for the latter.

From the sample selection models, the most important result is that one that associates the degree of truncation with mobility. A negative IMR leads to downward shifts in wages of those who self – selected which then translates into wage disadvantage. In the results, the negativity of the IMR is associated with models that also control for parental educational achievements. Thus, because of the role of parental education or its correlates such as wages, it can be argued that improving the household's educational profile is indeed important in improving mobility.

As argued in studies on mobility, resources play an important role in educational success. It has been established that non – labor income continue to play a central role in labor market decisions. In one of our empirical investigations, contributions from abroad or remittances drive this significant influence. Because of the importance of education in most migrant households, investments in children's education have become more strategic than ever. We now know that in determining educational achievements, the effect of non – labor income is not uniformly distributed across educational outcomes and gender. Rather, it's positive effect can only be observed for those who finish college. This may provide preliminary evidence that households prioritize college education, pouring resources to defray costs of college education as a way to ensure mobility. On the other hand, a high non – labor income may also

discourage workers from securing employment, a common empirical result indicating that potential workers may be better off waiting for optimal wage offers given that resources permit them to lengthen job search to improve matching.

There is no doubt that we are missing a lot of factors, observed and unobserved, that may play critical roles in achieving upward mobility. The degree of social mobility in any given society is the result of a dynamic process closely intertwined with the evolution of public policy and other complex social processes that undoubtedly emanates from the family. Understandably, the missing or generally unobserved factors are equally as important as the known ones, specifically educational achievement, occupational status, and household resources proxied by nonlabor income. In a policy paper that the Philippines may wish to emulate, (Corak, 2013) pointed out that socio economic background holds tremendous influence on child development, from in utero to early childhood years. Based on this, government programs like the 4Ps present a good strategy to limit inequality of access of expectant mothers to proper counselling, improve nutrition balance to prevent stunting and better health monitoring. There should also be programs based on family initiatives that will ensure greater participation among mothers through the establishment of day care centers and other programs that help improve the quality of parental inputs towards young children, especially in poor households.

The benefits of such early interventions or initiatives go beyond economic success. Household dynamics between poor and richer households are simply different not only in the amount of resources chosen to be spent on the education and upbringing on children but also from over all family culture. The Philippines suffer from high drop – out rates, thereby seriously limiting over – all mobility. Clearly, there exist policy tensions with respect to the timing and effectiveness of interventions. In their review, Heckman, Stixrud, & Urzua (2006) note the importance of the active role of parents in developing their children's cognitive and noncognitive skills, which have been proven instrumental in ensuring persistence in ability differences. They remarked that early interventions, enriched with home visitations for disadvantaged children with high likelihood of dropping out of school may lead to better labor market outcomes and even lower incidence of other societal problems such as criminality. Apparently, interventions should not only be anchored on the strategy that cognitive skills should be prioritized, as evidence from the Perry Preschool Program highlighted the importance of developing non-cognitive traits. Legislation can also help in creating a good environment for the newborn. A notable example is the legislative initiative to extend the duration of maternity leaves to 100 days. But this initiative needs to be on guard against possible discrimination and other malpractices by ensuring job security.

In sum, improving mobility in the labor market necessitates that the government need to pay close attention to trends or factors that may stymie upward mobility. Because labor market participation is an important way for households to earn, efforts to increase labor force participation rates should be doubled. Participation in the labor market depends on educational achievements, potential earnings, perceptions of relative rewards and penalties, prevalence of discriminatory practices, regional structures, and household resources. In the literature, economists distinguish earnings from household income, as the former depends on returns to education and labor market luck. If women are known to have higher propensities

to finish college education relative to their male counterparts, then such an observation could be used to improve their profile in the labor market. It should be emphasized that the ability to seize on market determined luck is to have high quality educational systems and mechanisms that sustainably support family life, especially those who find it hard to substitute quality time for children in favor of continued labor market engagement. While it is true that women from different regions graduate from college with high likelihood, it may be the case that those who graduate from high quality institution are better prepared to tackle changes in labor market trends.

6. Concluding remarks

This paper provides a partial characterization of mobility in the labor market. Measurements and various estimation strategies were operationalized using parents – offspring sample pairs that were constituted using various rounds of Labor Force Survey and Family Income and Expenditure Survey.

Wage persistence may be a central characterization the Philippine labor market. While econometric shortcomings of Mincerian equations are acknowledged, evidence consistently show that parental education has a dominant effect on wage outcomes of children. Wage premia associated with children with well-educated fathers are robustly high. On the other hand, wage penalties accruing to children with less educated parents have been consistently high.

Taking stock of period specific wage distributions, estimated transition probabilities confirm persistence at the lowest and highest quintiles. The transition probabilities show that persistence is not uniformly observed throughout the reference distribution. Rather, such results confirm the plausible non – linearity of mobility estimates. The results also show that the probability that daughters will be located in the lowest quintile of their father's distribution is lower than when the reference distribution belongs to their mothers.

The paper also fit models that effectively avoided biases and errors associated with wage data. Such models use permanent income proxies in the form of educational achievements. Results are promising and reflective of past evidence. They still show that parental education exerts a considerable influence on the likelihood that a sons or daughter will finish college. The nature of the ordered probit model allows us to contend that parameter estimates may represent measures associated with intergenerational education persistence (as shown in Table A17). Resources in the form of contributions from abroad or remittances play a critical role in improving the chance that a son or daughter will finish college. Disparities in economic status, proxied by poverty status are reflected in significant statistical differences in terms of educational outcomes. The finding that the relative probability of sons or daughters to obtain a college degree is higher in nonpoor than poor households only confirm the importance of family resources in helping ensure higher mobility for children.

In terms of selectivity, evidence point to the presence of limited mobility. The most important result is the one that associates the degree of truncation with mobility. Selection models that incorporate parental information like education and wages yield results that prove to be different from usual selection models that only control for the wage earners' attributes. The estimated truncation effect in models that control for parental attributes is usually negative

and significant, thereby implying downward shifts in wages relative to their randomly drawn counterparts. Thus, results do lend support to models that predict lower wages for children whose fathers have low educational achievements.

While we need panel data to identify the degree of mobility, it is clear that there are trends or developments in the labor market that may be informative as to how they will affect such a transition. First, as documented in a World Bank study, trends show that real daily earnings are falling. Falling wages may delay participation in the labor market. Second, part – time employment remains significant especially in agriculture, transportation and retail trade. Third, unemployment spells still afflict the youth and women. Fourth, a large proportion of the women population is simply not participating in the labor market. Fifth, underemployment continues to be high especially in regional labor markets. Thus, unemployment, underemployment, and limited labor force participation adversely affect mobility. Even employed workers in sectors that have slow wage growth can contribute to limited mobility.

Recognizing that high mobility cannot be achieved in the short – run is crucial. It's a long term goal. There are simply too many factors that determine the pace of mobility that form way before the individual has decided to enter the labor market. Countering the problem of low mobility fundamentally necessitates not only active labor market programs that may either provide stop – gap measures or promote sustainable employment, high productivity and improve matching but more importantly, progressive policies that have long term implications which are expected to enhance human capital accumulation, foster skill development, improve labor market earnings and render effective early interventions that will develop cognitive and non – cognitive skills. There should be a mobility initiative or blueprint to render coherent all policies expected to promote regional economic growth, uplift the life of the disadvantaged, improve the employability of the youth and women through innovative internship and job programs, reduce market discrimination and promote equality of opportunities, and sustain family – based programs that ensure proper nutrition, guidance and delivery of other forms of support.

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Table A1 Predicted probabilities associated with attaining college education: Sample pairs

	Father's Education				Mother's Education			
	Sons		Daughters		Sons		Daughters	
HGC	CG2006	CG2009	CG2006	CG2009	CG2006	CG2009	CG2006	CG2009
NGC	0.073	0.055	0.189	0.179	0.065	0.080	0.166	0.168
EU	0.112	0.103	0.303	0.278	0.093	0.091	0.284	0.286
EG	0.139	0.138	0.345	0.331	0.142	0.150	0.347	0.334
HSU	0.187	0.168	0.393	0.378	0.175	0.175	0.369	0.392
HSG	0.227	0.231	0.422	0.441	0.224	0.238	0.452	0.408
CU	0.288	0.328	0.575	0.512	0.321	0.303	0.519	0.512
CG	0.377	0.442	0.632	0.650	0.402	0.419	0.689	0.663

Note: Probability estimates pertain to matched education achievements of father – daughter, father – sons, mother – daughters and mother – sons.

Table A2 Education and occupation (values in percent)

	Father's occupation							Son's occupation							Daughters occupation						
Overall	HGP	LGP	NMC	Skilled	Farmers	Semi - skilled	Low skilled	HGP	LGP	NMC	Skilled	Farmers	Semi - skilled	Low skilled	HGP	LGP	NMC	Skilled	Farmers	Semi - skilled	Low skilled
NGC	1.824	0.428	0.324	0.734	81.997	1.788	12.905	0.562	0.382	1.334	1.301	25.203	2.087	69.131	3.874	0.000	5.199	0.000	9.684	3.575	77.667
EU	4.045	0.457	1.868	4.233	62.520	7.042	19.836	0.580	0.117	2.858	3.099	13.211	3.336	76.797	2.559	0.275	9.268	0.795	4.875	2.347	79.881
EG	6.154	0.745	2.945	8.467	50.957	11.470	19.261	1.012	0.194	4.677	4.915	10.447	5.601	73.156	2.599	0.606	15.654	0.961	2.567	7.034	70.579
HSUG	8.699	1.759	4.538	13.141	38.097	16.419	17.346	1.347	0.446	8.094	7.121	7.706	6.375	68.910	2.906	0.886	25.954	1.071	2.227	5.136	61.820
HSG	13.091	3.052	8.022	16.314	28.464	16.250	14.810	2.321	1.335	14.759	11.403	6.283	9.551	54.349	4.400	2.234	40.341	8.802	1.177	7.214	35.836
CUG	20.351	7.859	14.737	14.806	21.037	12.512	8.696	4.722	5.318	25.807	13.500	4.804	9.939	35.911	7.687	6.342	51.943	7.403	0.798	4.001	21.826
CG	46.934	19.703	12.877	3.208	11.269	3.645	2.362	27.286	17.139	33.206	5.018	1.896	3.870	11.587	34.831	14.610	43.896	1.874	0.184	0.877	3.728
Urban																					
NGC	5.166	0.347	1.551	1.313	57.124	5.746	28.750	0.697	0.000	7.179	5.421	13.776	8.584	64.340	11.532	0.000	27.262	0.000	0.000	12.738	48.468
EU	8.060	0.937	4.234	9.258	38.294	15.084	24.136	1.506	0.337	6.248	5.100	15.150	7.615	64.046	4.622	0.968	20.936	1.662	2.179	3.468	66.166
EG	9.442	0.937	5.136	15.307	26.920	19.700	22.560	1.550	0.528	8.484	7.672	8.542	10.391	62.831	3.395	2.015	26.096	2.476	1.124	9.174	55.719
HSUG	12.452	2.834	7.042	20.071	15.421	23.824	18.359	2.414	0.919	13.857	11.169	4.957	11.818	54.867	5.374	2.019	39.664	2.231	1.006	7.122	42.584
HSG	16.654	3.990	10.558	20.990	12.689	19.930	15.184	2.912	2.316	21.249	15.071	3.552	14.004	40.899	4.044	3.598	42.757	13.540	0.498	9.224	26.339
CUG	23.881	9.618	16.546	17.263	9.305	14.536	8.851	5.454	7.071	32.811	14.575	1.952	11.897	26.239	6.504	7.612	55.673	9.357	0.071	4.946	15.836
CG	50.140	22.383	13.159	3.663	5.124	3.568	1.961	28.610	20.269	35.029	4.486	0.852	3.888	6.866	32.381	16.841	45.394	1.962	0.068	0.719	2.631
Rural																					
NGC	1.375	0.426	0.218	0.639	85.153	1.272	10.916	0.470	0.413	0.373	0.606	27.214	0.783	70.139							
EU	2.822	0.313	1.133	2.695	69.904	4.615	18.519	0.358	0.068	2.063	2.615	12.765	2.362	79.769	2.151	0.091	5.423	0.540	6.588	1.896	83.313
EG	4.520	0.650	1.856	5.118	62.836	7.403	17.617	0.841	0.094	3.459	4.044	11.028	4.104	76.430	2.033	0.051	11.446	0.502	3.638	6.438	75.890
HSUG	5.951	0.981	2.737	8.111	54.537	11.068	16.616	0.875	0.246	5.551	5.402	8.898	4.019	75.011	2.307	0.299	16.485	0.561	2.961	4.196	73.193
HSG	8.738	1.910	4.941	10.628	47.760	11.734	14.289	1.933	0.687	10.526	9.013	8.065	6.648	63.127	3.648	0.788	33.009	3.461	2.232	5.071	51.790
CUG	14.043	4.727	11.463	10.506	41.974	8.944	8.344	3.834	3.181	17.196	12.195	8.279	7.587	47.729	7.693	3.603	44.799	5.006	1.617	3.636	33.646
CG	37.833	12.386	12.276	1.955	27.994	3.997	3.560	24.006	10.019	29.324	6.228	4.303	3.772	22.347	32.087	7.892	42.870	1.699	0.688	1.339	13.424

Note: Values are estimated proportions using survey data estimation method. The values represent the distribution of respondents who finished a certain level of education across occupational categories.

Table A3 Average proportions of sons/daughters completing an education level, by father's education (values in percent)

	Father - son pairs								Father - daughter pairs						
Overall	NGC	EU	EG	HSUG	HSG	CUG	CG		NGC	EU	EG	HSUG	HSG	CUG	CG
NGC	14.783	41.607	16.673	12.923	9.540	3.447	1.031		11.301	27.153	19.091	15.799	17.107	5.707	3.842
EU	1.259	32.320	18.403	20.657	19.476	5.524	2.360		1.010	12.497	12.345	19.316	33.104	11.799	9.929
EG	0.651	10.834	20.926	23.440	30.336	9.343	4.469		0.422	3.356	8.622	14.907	39.869	16.356	16.469
HSUG	0.477	9.439	11.693	27.006	31.309	13.586	6.492		0.383	2.704	4.502	16.510	33.606	21.807	20.490
HSG	0.505	2.944	5.830	16.349	41.049	20.697	12.626		0.410	0.916	1.790	7.177	34.926	24.399	30.384
CUG	0.349	1.771	2.879	11.222	24.656	32.549	26.573		0.160	0.533	0.527	4.620	17.119	25.474	51.567
CG	0.292	0.454	0.896	4.080	11.165	24.150	58.964		0.320	0.348	0.174	1.764	5.732	15.236	76.424
Urban															
NGC	10.321	32.707	19.064	10.983	17.582	5.505	3.836		1.644	14.868	19.732	16.376	33.311	7.366	6.703
EU	0.817	24.261	14.490	22.054	24.864	9.214	4.300		0.754	7.382	7.319	15.426	40.320	15.844	12.957
EG	0.664	8.502	17.829	21.774	33.151	12.084	5.995		0.104	2.509	7.001	11.197	40.869	18.353	19.967
HSUG	0.394	7.019	8.679	25.410	32.459	17.201	8.842		0.374	2.053	2.747	15.683	33.990	23.083	22.071
HSG	0.478	2.188	4.773	14.039	40.500	23.229	14.794		0.298	0.690	1.273	5.689	34.756	24.773	32.519
CUG	0.250	1.080	2.454	9.028	22.137	35.581	29.466		0.200	0.376	0.417	3.377	16.076	26.269	53.289
CG	0.315	0.314	0.675	2.989	9.888	23.921	61.897		0.323	0.386	0.160	1.501	5.247	13.979	78.403
Rural															
NGC	15.389	42.674	16.380	13.239	8.620	3.048	0.651		13.036	29.250	19.166	15.723	14.499	5.179	3.147
EU	1.401	34.970	19.693	20.216	17.700	4.307	1.718		1.113	14.739	14.555	21.053	29.939	9.986	8.616
EG	0.649	12.074	22.553	24.339	28.849	7.883	3.657		0.647	3.969	9.768	17.503	39.176	14.904	14.034
HSUG	0.544	11.320	13.991	28.233	30.411	10.858	4.639		0.411	3.326	6.446	17.441	33.131	20.543	18.696
HSG	0.544	3.984	7.224	19.401	41.743	17.387	9.717		0.614	1.331	2.731	9.891	35.176	23.757	26.503
CUG	0.534	3.165	3.721	15.710	29.651	26.444	20.773		0.062	0.922	0.805	7.814	19.866	23.357	47.176
CG	0.214	0.868	1.574	7.301	14.853	24.681	50.504		0.295	0.227	0.257	2.687	7.400	19.720	69.413

Note: All estimates were arrived at using survey estimation methods for proportions, then averaged over the period spanning 2003 – 2009. Estimates pertain to the proportion of sons and daughters who finished a certain level of education given a particular educational attainment of their father. The results refer to overall estimates, meaning no distinction of households based on the number of sons and daughters was made.

Table **A**4 Average proportions of sons/daughters completing an education level, by father's education (values in percent)

	Father - son pairs								Father - daughter pairs						
NS=1	NGC	EU	EG	HSUG	HSG	CUG	CG		NGC	EU	EG	HSUG	HSG	CUG	CG
NGC	15.919	40.074	18.011	12.518	8.823	3.727	0.928		10.567	27.331	18.184	15.473	17.666	6.533	4.245
EU	1.308	30.559	17.030	21.430	20.544	6.295	2.836		1.269	12.741	12.679	19.679	33.169	11.457	9.008
EG	0.704	9.736	18.454	23.970	31.861	10.152	5.122		0.477	3.413	8.521	15.360	39.230	17.077	15.919
HSUG	0.551	8.271	10.313	26.819	30.899	15.629	7.518		0.504	2.522	4.410	16.854	33.034	21.903	20.771
HSG	0.448	2.706	5.224	16.077	39.764	21.310	14.473		0.481	0.827	1.696	7.592	34.876	24.176	30.350
CUG	0.533	1.559	2.655	10.673	23.393	33.286	27.900		0.166	0.669	0.488	4.488	17.180	25.677	51.330
CG	0.440	0.276	0.792	3.253	9.265	24.173	61.804		0.360	0.333	0.158	1.946	5.013	15.283	76.906
NS=2															
NGC	13.481	43.321	14.570	13.499	9.875	4.552	0.703		12.788	26.410	19.900	16.767	15.866	5.379	2.888
EU	1.094	33.484	19.551	19.779	18.636	5.279	2.174		0.523	12.060	12.119	19.606	32.321	12.249	11.128
EG	0.461	10.861	21.570	22.873	30.663	9.369	4.203		0.368	3.476	8.796	14.477	41.156	14.215	17.511
HSUG	0.487	9.380	12.989	27.449	31.540	12.272	5.882		0.253	3.159	4.417	16.691	34.043	21.117	20.317
HSG	0.488	2.955	5.656	15.540	42.941	20.860	11.560		0.330	1.164	1.911	6.792	35.140	25.109	29.554
CUG	0.112	1.882	2.841	10.432	25.831	33.017	25.886		0.208	0.419	0.833	4.702	16.207	25.801	51.829
CG	0.098	0.612	0.969	4.428	13.064	23.864	56.967		0.259	0.438	0.291	1.080	7.366	15.453	75.114

Note: All estimates were arrived at using survey estimation methods for proportions, then averaged over the period spanning 2003 – 2009. Estimates pertain to the proportion of sons and daughters who finished a certain level of education given a particular educational attainment of their father. The results are based on household subpopulations where the number of sons or daughters is either NS=1 and NS=2, respectively. Separate estimates may be given, upon request for household with more than 2 sons or daughters.

Table A5 Father -children occupation, by urbanity (values in percent)

	Father - son pairs								Father - daughter pairs						
Overall	High grade professionals	Lower grade professionals	Non manual and clerical workers	Skilled workers	Farmers	Semi - skilled workers	Low skilled workers		High grade professionals	Lower grade professionals	Non manual and clerical workers	Skilled workers	Farmers	Semi - skilled workers	Low skilled workers
High grade professionals	14.561	6.551	27.709	10.897	4.301	8.002	27.980		23.023	10.153	46.591	3.917	0.222	2.909	13.184
Lower grade professionals	12.839	18.549	26.300	9.818	3.794	6.840	21.859		23.750	18.391	42.513	3.667	0.456	1.762	9.461
Non manual and clerical workers	7.166	5.836	33.490	10.504	4.327	7.486	31.194		15.850	8.659	48.430	6.283	0.544	3.937	16.300
Skilled workers	3.418	3.840	20.487	23.680	4.040	8.636	35.899		12.464	6.599	52.011	7.250	0.343	3.950	17.386
Farmers	1.754	0.786	5.095	4.768	11.886	3.040	72.671		9.143	2.376	25.230	3.080	2.734	3.981	53.457
Semi - skilled workers	2.736	2.473	16.174	8.530	5.164	23.809	41.113		10.039	6.364	45.037	7.174	0.776	8.202	22.409
Low skilled workers	1.588	0.880	9.834	4.790	4.092	4.932	73.887		6.660	2.655	37.864	3.511	0.971	4.578	43.761
Urban															
High grade professionals	17.183	9.311	31.914	10.180	1.942	8.799	20.673		23.629	12.396	46.774	4.303	0.000	2.854	10.043
Lower grade professionals	14.883	22.907	26.446	8.556	1.755	7.383	18.071		23.490	18.791	42.779	4.166	0.000	2.235	8.536
Non manual and clerical workers	8.325	7.510	35.909	10.220	1.998	8.505	27.534		15.969	10.190	49.907	7.538	0.202	3.603	12.587
Skilled workers	4.283	4.841	23.846	24.069	2.387	10.005	30.573		11.539	7.921	52.020	8.720	0.161	4.795	14.846
Farmers	3.353	1.788	8.952	7.722	13.308	5.342	59.536		12.953	4.815	33.687	8.095	1.596	5.849	33.006

Semi - skilled workers	3.153	3.513	20.136	9.717	2.307	25.844	35.330		9.727	7.890	47.504	8.235	0.149	8.196	18.297
Low skilled workers	2.534	1.737	15.691	6.121	2.631	7.588	63.697		7.834	3.986	44.139	5.361	0.341	5.335	33.006
Rural															
High grade professionals	10.076	1.774	20.434	12.105	8.401	6.642	40.569		21.829	4.691	45.846	3.057	0.823	2.938	20.817
Lower grade professionals	7.507	7.259	25.991	13.144	9.127	5.371	31.600		24.697	16.338	41.104	1.851	1.994	0.000	14.015
Non manual and clerical workers	5.174	2.834	29.110	11.128	8.534	5.577	37.641		15.820	4.710	45.210	3.068	1.338	4.634	25.220
Skilled workers	2.038	2.352	15.420	23.109	6.551	6.582	43.951		14.544	3.779	51.926	3.978	0.822	1.986	22.966
Farmers	1.458	0.599	4.384	4.226	11.620	2.625	75.087		8.226	1.775	23.191	1.860	3.008	3.518	58.423
Semi - skilled workers	2.170	1.083	11.034	7.094	8.849	21.307	48.461		10.733	3.439	40.031	5.161	1.988	8.259	30.391
Low skilled workers	1.074	0.408	6.598	4.055	4.894	3.461	79.510		5.471	1.442	32.126	1.801	1.538	3.879	53.746

Note: Values are estimated proportions using survey data estimation method. The values represent the distribution of fathers who belong to a certain occupational category across occupations of sons or daughters.

Table A6 Household composition: Father -children occupation, by urbanity

	Father - son pairs								Father - daughter pairs						
NS=1	High grade professionals	Lower grade professionals	Non manual and clerical workers	Skilled workers	Farmers	Semi - skilled workers	Low skilled workers		High grade professionals	Lower grade professionals	Non manual and clerical workers	Skilled workers	Farmers	Semi - skilled workers	Low skilled workers
High grade professionals	15.501	7.606	28.757	9.759	4.239	7.821	26.316		23.086	9.914	47.919	3.250	0.323	2.687	12.817
Lower grade professionals	15.256	19.359	26.100	9.350	4.370	6.546	19.019		23.139	19.556	42.567	4.079	0.193	2.519	7.948
Non manual and clerical workers	8.586	6.051	35.921	10.683	4.319	6.143	28.296		17.529	8.013	47.194	6.466	0.354	3.369	17.077
Skilled workers	4.323	4.512	21.516	23.709	4.433	8.014	33.491		12.246	5.671	54.201	6.474	0.265	3.726	17.417
Farmers	1.916	0.698	5.572	5.072	12.485	2.927	71.329		9.575	2.233	25.651	2.890	3.075	3.787	52.786
Semi - skilled workers	3.393	2.814	16.367	8.844	5.433	23.644	39.506		10.301	5.661	46.556	6.256	0.910	7.387	22.927
Low skilled workers	1.759	0.968	10.686	4.942	4.351	4.973	72.319		7.025	2.219	36.954	3.521	1.312	4.361	44.606
NS=2															

High grade professionals	15.189	5.796	25.926	11.891	4.305	6.982	29.911		23.551	10.306	44.801	4.548	0.000	2.886	13.904
Lower grade professionals	11.011	18.426	26.607	11.205	3.250	6.482	23.020		23.526	16.970	41.051	2.389	1.012	0.810	14.241
Non manual and clerical workers	6.241	5.150	32.144	9.546	4.059	10.323	32.537		12.268	10.744	52.826	5.970	1.240	4.034	12.920
Skilled workers	3.026	3.512	20.466	23.879	3.067	9.060	36.991		12.232	8.041	48.833	8.229	0.631	3.572	18.463
Farmers	1.573	0.725	4.826	4.979	11.824	3.070	73.003		8.578	2.676	24.030	2.892	2.374	4.273	55.180
Semi - skilled workers	1.758	2.739	15.813	7.743	5.305	24.104	42.536		9.934	7.481	43.337	6.216	0.711	8.854	23.466
Low skilled workers	1.431	0.975	9.797	5.060	3.719	4.587	74.431		7.046	4.014	38.461	3.098	0.273	3.715	43.391

Note: Values are estimated proportions using survey data estimation method. The values pertain to distribution of fathers who belong to a certain occupational category across occupations of sons or daughters.

Table **A7** Elasticity estimates for father – son data pairs

Year	OLS	IV	OLS-1	IV-1	OLS-2	IV-2	OLS-3	IV-3	OLS-4	IV-4	OLS-5	IV-5	OLS-6	IV-6	OLS-7	IV-7
2003	0.475	0.538	0.461	0.571	0.531	0.508	0.427	0.554	0.395	0.435	0.600	0.482	0.416	0.510	0.354	0.502
	0.000	0.001	0.002	0.002	0.005	0.006	0.003	0.003	0.011	0.016	0.008	0.012	0.004	0.004	0.010	0.017
2004	0.464	0.538	0.520	0.645	0.413	0.496	0.544	0.641	0.610	0.393	0.371	0.578	0.474	0.555	0.584	0.640
	0.001	0.001	0.003	0.003	0.029	0.048	0.002	0.004	0.048	0.079	0.048	0.094	0.005	0.007	0.004	0.006
2005	0.489	0.529	0.497	0.505	0.550	0.553	0.470	0.471	0.368	0.311	0.659	0.911	0.430	0.424	0.529	0.543
	0.001	0.001	0.002	0.002	0.004	0.007	0.003	0.003	0.020	0.037	0.048	0.079	0.003	0.004	0.019	0.019
2006	0.515	0.605	0.582	0.733	0.713	0.836	0.531	0.684	0.725	0.711	0.435	0.758	0.508	0.706	0.512	0.496
	0.003	0.002	0.002	0.003	0.009	0.017	0.002	0.003	0.016	0.037	0.090	0.170	0.002	0.007	0.005	0.009
2007	0.487	0.527	0.474	0.575	0.626	0.615	0.452	0.548	0.523	0.484	0.910	0.683	0.435	0.544	0.281	0.353
	0.000	0.001	0.001	0.003	0.005	0.010	0.002	0.004	0.006	0.015	0.028	0.046	0.003	0.008	0.008	0.009
2008	0.431	0.554	0.426	0.559	0.681	0.549	0.357	0.497	0.769	0.677	0.563	0.355	0.323	0.460	0.263	0.364
	0.001	0.001	0.002	0.003	0.009	0.018	0.002	0.003	0.101	0.100	0.007	0.027	0.002	0.004	0.009	0.011
2009	0.440	0.559	0.435	0.576	0.436	0.786	0.422	0.537	0.712	0.699	-0.010	0.595	0.337	0.467	0.336	0.332
	0.001	0.002	0.003	0.003	0.022	0.013	0.003	0.003	0.007	0.011	0.078	0.126	0.006	0.007	0.010	0.018
	OLS-8	IV-8	OLS-9	IV-9	OLS-10	IV-10	OLS-11	IV-11	OLS-12	IV-12	OLS-13	IV-13	OLS-14	IV-14	OLS-15	IV-15
2003	0.395	0.435	0.416	0.510	0.600	0.482	0.354	0.502	0.381	0.465	0.360	0.481	0.309	0.321	0.434	0.520
	0.011	0.016	0.004	0.004	0.008	0.012	0.010	0.017	0.010	0.023	0.006	0.009	0.228	0.142	0.006	0.006
2004	0.610	0.393	0.474	0.555	0.371	0.578	0.584	0.640	1.091	1.223	0.803	1.041	-0.043	-0.043	0.449	0.507
	0.048	0.079	0.005	0.007	0.048	0.094	0.004	0.006	0.017	0.023	0.089	0.129	0.506	0.513	0.004	0.005
2005	0.368	0.311	0.430	0.424	0.659	0.911	0.529	0.543	0.509	0.611	0.469	0.849	-0.099	-0.099	0.423	0.402
	0.020	0.037	0.003	0.004	0.048	0.079	0.019	0.019	0.015	0.029	0.048	0.232	0.087	0.104	0.003	0.003
2006	0.725	0.711	0.508	0.704	0.435	0.758	0.512	0.496	0.772	0.751	0.222	0.273	0.462	0.825	0.532	0.701
	0.016	0.037	0.002	0.007	0.090	0.170	0.005	0.009	0.015	0.032	0.014	0.014	2.850	78.422	0.003	0.006
2007	0.523	0.484	0.435	0.544	0.921	0.681	0.281	0.353	0.558	0.498	0.448	0.317	0.599	0.610	0.422	0.508
	0.006	0.015	0.003	0.008	0.018	0.045	0.008	0.009	0.012	0.014	0.016	0.052	0.036	0.050	0.003	0.009
2008	0.769	0.677	0.323	0.460	0.563	0.355	0.263	0.364	0.840	0.831	0.417	0.436	-0.499	-0.499	0.308	0.424
	0.101	0.100	0.002	0.004	0.007	0.027	0.009	0.011	0.027	0.044	0.011	0.021	0.364	0.372	0.002	0.005

2009	0.712	0.699	0.337	0.467	-0.010	0.595	0.336	0.332	0.545	0.483	0.069	0.007	0.873	0.931	0.363	0.524
	0.007	0.011	0.006	0.007	0.078	0.126	0.010	0.018	0.008	0.011	0.007	0.019	0.068	0.112	0.006	0.008

Note: Elasticity estimates (in black) and standard error (in red) were arrived at using bootstrap based method. The following sample restrictions were used:
1 – age restriction on sons/daughters (25 – 35)
2 – age restriction on sons/daughters (25 -35) & father's job status is non - permanent.
3 - age restriction on sons/daughters (25 -35) & father's job status is permanent.
4 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in urban area
5 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in rural area
6 - age restriction on sons/daughters (25 – 35) & father's job status is permanent & household resides in urban area
7 - age restriction on sons/daughters (25 – 35) & father's job status is permanent & household resides in rural area
8 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in urban area
9 - age restriction on sons/daughters (25 – 35) father's job status is permanent & household resides in urban area
10 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in rural area
11 - age restriction on sons/daughters (25 – 35) & father's job status is permanent & household resides in rural area
12 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in urban area & son's job status is non - permanent
13 - age restriction on sons/daughters (25 – 35) & father's job status is permanent & household resides in urban area & son's job status is non - permanent
14 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in rural area & son's job status is permanent
14 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in urban area & son's job status is permanent
15 - age restriction on sons/daughters (25 – 35) & father's job status is permanent & household resides in urban area & son's job status is permanent

Table A8 Elasticity estimates for father – daughter data pairs

Year	OLS	IV	OLS-1	IV-1	OLS-2	IV-2	OLS-3	IV-3	OLS-4	IV-4	OLS-5	IV-5	OLS-6	IV-6	OLS-7	IV-7
2003	0.488	0.648	0.398	0.545	0.788	0.613	0.341	0.491	0.449	0.309	1.257	1.257	0.352	0.548	0.344	0.297
	0.002	0.004	0.006	0.006	0.008	0.012	0.006	0.006	0.049	0.048	18.410	17.520	0.010	0.010	0.016	0.023
2004	0.412	0.733	0.329	0.644	0.518	0.234	0.252	0.489	0.256	0.311	0.514	0.344	0.273	0.496	0.033	0.118
	0.002	0.005	0.006	0.011	0.178	0.314	0.007	0.010	0.320	0.294	0.501	0.630	0.007	0.016	0.039	0.056
2005	0.489	0.657	0.417	0.508	0.476	0.616	0.410	0.484	0.835	0.823	0.254	0.074	0.309	0.313	0.626	0.818
	0.002	0.004	0.004	0.007	0.031	0.025	0.004	0.007	0.121	0.127	0.119	0.129	0.005	0.009	0.006	0.013
2006	0.506	0.676	0.521	0.578	0.318	0.614	0.522	0.561	0.242	0.212	0.728	0.715	0.435	0.453	0.433	0.694
	0.004	0.004	0.006	0.012	0.028	0.054	0.006	0.015	0.038	0.057	0.138	0.121	0.008	0.014	0.092	0.123
2007	0.528	0.785	0.515	0.646	0.078	0.011	0.489	0.621	0.468	0.314	-0.241	0.019	0.450	0.558	0.348	0.397
	0.002	0.006	0.003	0.006	0.015	0.070	0.003	0.006	0.037	0.044	0.023	0.076	0.005	0.008	0.005	0.009
2008	0.483	0.668	0.492	0.627	0.691	1.547	0.463	0.610	0.370	0.417	1.060	1.990	0.466	0.566	0.379	0.547
	0.001	0.003	0.003	0.005	0.026	0.217	0.003	0.006	0.028	0.252	0.213	0.659	0.004	0.008	0.015	0.017
2009	0.410	0.615	0.356	0.539	0.346	0.709	0.343	0.460	0.048	0.179	2.848	2.848	0.267	0.407	0.520	0.530
	0.002	0.004	0.004	0.009	0.083	0.108	0.004	0.007	0.300	0.346	0.000	0.000	0.006	0.011	0.021	0.032
	OLS-8	IV-8	OLS-9	IV-9	OLS-10	IV-10	OLS-11	IV-11	OLS-12	IV-12	OLS-13	IV-13	OLS-14	IV-14	OLS-15	IV-15
2003	0.449	0.309	0.352	0.548	1.257	1.257	0.344	0.297	-0.146	-0.146			-0.001	-0.001	0.382	0.569
	0.049	0.048	0.010	0.010	18.410	17.520	0.016	0.023	0.045	0.045			1.227	1.135	0.013	0.011
2004	0.256	0.311	0.273	0.496	0.514	0.344	0.033	0.118	-0.040	-0.100			0.291	0.291	0.274	0.535
	0.320	0.294	0.007	0.016	0.501	0.630	0.039	0.056	0.037	0.053			0.355	0.283	0.008	0.015
2005	0.835	0.823	0.309	0.313	0.254	0.074	0.626	0.818	-0.113	0.018			0.161	0.161	0.331	0.351
	0.121	0.127	0.005	0.009	0.119	0.129	0.006	0.013	0.028	0.031			0.403	0.663	0.006	0.009
2006	0.242	0.212	0.435	0.453	0.728	0.715	0.433	0.694	1.202	0.898			-1.117	-1.117	0.412	0.459
	0.038	0.057	0.008	0.014	0.138	0.121	0.092	0.123	0.591	0.478			8.100	10.129	0.007	0.013
2007	0.468	0.314	0.450	0.558	-0.241	0.019	0.348	0.397	0.614	0.635			0.388	0.388	0.411	0.512
	0.037	0.044	0.005	0.008	0.023	0.076	0.005	0.009	0.273	0.278			0.096	0.103	0.005	0.010
2008	0.370	0.417	0.466	0.566	1.060	1.990	0.379	0.547	0.069	-0.005			0.451	0.166	0.499	0.616
	0.028	0.252	0.004	0.008	0.213	0.659	0.015	0.017	0.047	0.069			0.047	0.561	0.005	0.009

2009	0.048	0.179	0.267	0.409	2.848	2.848	0.520	0.530	0.404	0.270			0.137	0.106	0.254	0.369
	0.300	0.346	0.006	0.011	0.000	0.000	0.021	0.032	0.258	0.366			0.101	0.141	0.007	0.013

Note: Elasticity estimates (in black) and standard error (in red) were arrived at using bootstrap based method. The following sample restrictions were used:
1 – age restriction on sons/daughters (25 – 35)
2 – age restriction on sons/daughters (25 -35) & father's job status is non - permanent.
3 - age restriction on sons/daughters (25 -35) & father's job status is permanent.
4 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in urban area
5 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in rural area
6 - age restriction on sons/daughters (25 – 35) & father's job status is permanent & household resides in urban area
7 - age restriction on sons/daughters (25 – 35) & father's job status is permanent & household resides in rural area
8 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in urban area
9 - age restriction on sons/daughters (25 – 35) father's job status is permanent & household resides in urban area
10 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in rural area
11 - age restriction on sons/daughters (25 – 35) & father's job status is permanent & household resides in rural area
12 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in urban area & son's job status is non - permanent
13 - age restriction on sons/daughters (25 – 35) & father's job status is permanent & household resides in urban area & son's job status is non - permanent
14 - age restriction on sons/daughters (25 – 35) & father's job status is non – permanent & household resides in urban area & son's job status is permanent
15 - age restriction on sons/daughters (25 – 35) & father's job status is permanent & household resides in urban area & son's job status is permanent

Table A9 Elasticity estimates for father - son pairs, by major island

	NCR		LUZON		VISAYAS		MINDANAO	
NCR	OLS	IV	OLS	IV	OLS	IV	OLS	IV
2003	0.282	0.576	0.393	0.431	0.468	0.546	0.349	0.325
	0.017	0.024	0.001	0.002	0.003	0.004	0.003	0.005
2004	0.348	0.704	0.423	0.427	0.473	0.566	0.256	0.376
	0.008	0.034	0.002	0.003	0.003	0.007	0.002	0.004
2005	0.514	0.732	0.431	0.445	0.458	0.498	0.414	0.487
	0.008	0.020	0.003	0.004	0.009	0.011	0.003	0.005
2006	0.726	1.092	0.510	0.501	0.396	0.466	0.323	0.430
	0.009	0.016	0.006	0.003	0.004	0.006	0.012	0.021
2007	0.328	0.585	0.493	0.486	0.471	0.571	0.389	0.381
	0.006	0.020	0.001	0.003	0.003	0.004	0.003	0.009
2008	0.550	0.705	0.476	0.569	0.361	0.477	0.265	0.312
	0.006	0.009	0.002	0.002	0.006	0.015	0.002	0.007
2009	0.412	0.533	0.394	0.520	0.450	0.549	0.305	0.380
	0.006	0.014	0.002	0.004	0.005	0.009	0.002	0.005

Note: Elasticity estimates (in black) and standard error (in red) were arrived at using bootstrap based method

Table A10 Elasticity estimates: above and below father's median wage

	Below Median					Above median			
	Sons		Daughters			Sons		Daughters	
	OLS	IV	OLS	IV		OLS	IV	OLS	IV
2003	0.462	0.559	0.266	0.118		0.413	0.587	0.383	0.621
	0.002	0.019	0.018	0.096		0.003	0.005	0.008	0.015
2004	0.487	0.622	0.309	-0.004		0.326	0.554	0.316	0.637
	0.004	0.026	0.018	0.109		0.005	0.008	0.005	0.010
2005	0.465	0.210	0.404	0.900		0.521	0.565	0.555	0.666
	0.008	0.040	0.009	0.069		0.003	0.006	0.005	0.015
2006	0.492	0.301	0.462	0.688		0.567	0.570	0.334	0.711
	0.011	0.045	0.011	0.106		0.014	0.010	0.014	0.017
2007	0.466	0.478	0.399	0.905		0.423	0.450	0.458	0.801
	0.003	0.013	0.011	0.069		0.002	0.006	0.007	0.017
2008	0.445	0.604	0.241	0.791		0.333	0.502	0.474	0.589
	0.004	0.012	0.011	0.048		0.003	0.007	0.003	0.008
2009	0.347	0.465	0.369	0.839		0.353	0.525	0.347	0.670
	0.003	0.020	0.010	0.061		0.005	0.007	0.005	0.014

Note: Elasticity estimates (in black) and standard error (in red) were arrived at using bootstrap based method

Table A11 Transition probability matrix: Father - children pairs

	Father - son pairs						Father - daughter pairs				
Overall							Overall				
Quintiles	Bottom 20%	2nd	3rd	4th	Top 20%		Bottom 20%	2nd	3rd	4th	Top 20%
Bottom 20%	0.493	0.186	0.153	0.110	0.058		0.364	0.228	0.184	0.138	0.085
2nd	0.295	0.177	0.190	0.186	0.151		0.241	0.207	0.204	0.189	0.158
3rd	0.206	0.154	0.191	0.217	0.231		0.182	0.187	0.206	0.213	0.211
4th	0.121	0.120	0.177	0.241	0.341		0.104	0.145	0.193	0.240	0.318
Top 20%	0.044	0.064	0.121	0.225	0.545		0.032	0.071	0.131	0.229	0.537
1 - son household							1 daughter - household				
Bottom 20%	0.488	0.177	0.152	0.116	0.066		0.383	0.220	0.187	0.132	0.079
2nd	0.286	0.165	0.184	0.191	0.173		0.257	0.200	0.208	0.181	0.154
3rd	0.210	0.146	0.182	0.215	0.248		0.195	0.184	0.213	0.208	0.200
4th	0.127	0.115	0.167	0.234	0.356		0.113	0.143	0.201	0.237	0.306
Top 20%	0.049	0.063	0.118	0.219	0.551		0.033	0.067	0.133	0.224	0.543
2 son - household							2 daughters - household				
Bottom 20%	0.510	0.188	0.150	0.102	0.049		0.350	0.230	0.195	0.140	0.085
2nd	0.309	0.183	0.194	0.181	0.134		0.307	0.222	0.203	0.157	0.111
3rd	0.213	0.158	0.197	0.218	0.214		0.234	0.198	0.211	0.192	0.166
4th	0.129	0.124	0.185	0.245	0.317		0.104	0.150	0.210	0.246	0.290
Top 20%	0.046	0.063	0.125	0.232	0.534		0.042	0.081	0.151	0.231	0.496

Note: Values pertaining to same quintile (on diagonal entries) for fathers and offspring represent average probability that a son or daughter will find himself or herself ranked in the same distribution as his or her father. Estimates for 1 and 2 son/daughter households were also provided to ascertain the degree of robustness. These are households where there are more than 1 sons or daughters.

Table A12 Transition probability matrix: Mother - children pairs

	Mother - son pairs						Mother - daughter pairs				
Overall							Overall				
Quintiles	Bottom 20%	2nd	3rd	4th	Top 20%		Bottom 20%	2nd	3rd	4th	Top 20%
Bottom 20%	0.451	0.216	0.149	0.114	0.070		0.417	0.227	0.167	0.123	0.065
2nd	0.382	0.216	0.164	0.139	0.098		0.291	0.218	0.194	0.174	0.123
3rd	0.206	0.186	0.184	0.204	0.220		0.134	0.161	0.193	0.238	0.274
4th	0.080	0.115	0.155	0.231	0.419		0.052	0.095	0.152	0.250	0.452
Top 20%	0.036	0.072	0.113	0.210	0.569		0.026	0.060	0.114	0.226	0.574
1 - son household							1 daughter - household				
Bottom 20%	0.449	0.211	0.146	0.116	0.078		0.434	0.224	0.160	0.120	0.062
2nd	0.376	0.210	0.161	0.143	0.110		0.302	0.217	0.189	0.174	0.119
3rd	0.205	0.180	0.177	0.202	0.235		0.132	0.159	0.189	0.242	0.278
4th	0.080	0.112	0.147	0.226	0.436		0.059	0.102	0.154	0.255	0.431
Top 20%	0.035	0.068	0.105	0.199	0.594		0.029	0.061	0.111	0.225	0.574
2 son - household							2 daughter - household				
Bottom 20%	0.451	0.224	0.157	0.108	0.060		0.367	0.231	0.179	0.139	0.083
2nd	0.366	0.232	0.176	0.139	0.087		0.268	0.216	0.196	0.181	0.139
3rd	0.220	0.204	0.200	0.197	0.179		0.172	0.168	0.186	0.216	0.259
4th	0.061	0.098	0.152	0.231	0.458		0.043	0.085	0.143	0.240	0.488
Top 20%	0.060	0.113	0.152	0.223	0.452		0.029	0.065	0.117	0.223	0.566

Note: Values pertaining to same quintile (on diagonal entries) for fathers and offspring represent average probability that a son or daughter will find himself or herself ranked in the same distribution as his or her father. Estimates for 1 and 2 son/daughter households were also provided to ascertain the degree of robustness. These are households where there are more than 1 sons or daughters.

Table A13 Estimated probabilities that a son will finish a certain level of education: 2006 and 2009

	Son's educational attainment:2006								Son's educational attainment:2009						
Father's Education	NGC	EU	EG	HU	HG	CU	CG		NGC	EU	EG	HU	HG	CU	CG
NGC	0.034	0.167	0.150	0.165	0.268	0.138	0.078		0.037	0.198	0.139	0.170	0.270	0.127	0.058
	0.007	0.020	0.011	0.007	0.012	0.014	0.014		0.009	0.025	0.010	0.007	0.015	0.016	0.013
EU	0.020	0.125	0.128	0.156	0.286	0.171	0.114		0.018	0.131	0.113	0.157	0.301	0.176	0.104
	0.002	0.007	0.006	0.007	0.007	0.007	0.008		0.002	0.007	0.006	0.007	0.007	0.007	0.008
EG	0.015	0.104	0.116	0.147	0.291	0.188	0.138		0.011	0.101	0.097	0.145	0.307	0.201	0.137
	0.002	0.006	0.006	0.006	0.008	0.007	0.009		0.002	0.006	0.005	0.006	0.008	0.007	0.008
HSU	0.009	0.075	0.094	0.131	0.291	0.214	0.185		0.008	0.082	0.085	0.134	0.306	0.219	0.167
	0.002	0.006	0.006	0.006	0.008	0.008	0.012		0.001	0.007	0.006	0.007	0.008	0.008	0.012
HSG	0.006	0.058	0.079	0.118	0.284	0.230	0.225		0.004	0.053	0.063	0.110	0.292	0.247	0.231
	0.001	0.005	0.005	0.006	0.007	0.008	0.012		0.001	0.005	0.004	0.006	0.008	0.008	0.011
CU	0.003	0.040	0.061	0.099	0.267	0.245	0.285		0.002	0.029	0.041	0.081	0.257	0.266	0.326
	0.001	0.006	0.006	0.007	0.009	0.009	0.019		0.000	0.004	0.004	0.006	0.009	0.008	0.018
CG	0.002	0.023	0.041	0.074	0.233	0.253	0.374		0.001	0.014	0.023	0.053	0.206	0.264	0.440
	0.000	0.004	0.005	0.007	0.011	0.008	0.024		0.000	0.003	0.003	0.006	0.012	0.008	0.025
Mother's Education															
NGC	0.037	0.178	0.156	0.168	0.265	0.129	0.067		0.025	0.157	0.124	0.163	0.289	0.156	0.086
	0.007	0.019	0.010	0.007	0.012	0.014	0.012		0.006	0.021	0.010	0.008	0.011	0.016	0.016
EU	0.023	0.135	0.136	0.161	0.286	0.161	0.098		0.022	0.148	0.120	0.161	0.293	0.163	0.093
	0.003	0.008	0.007	0.007	0.007	0.007	0.008		0.003	0.008	0.006	0.007	0.007	0.007	0.008
EG	0.013	0.096	0.112	0.146	0.296	0.195	0.142		0.010	0.094	0.092	0.140	0.305	0.208	0.152
	0.002	0.006	0.006	0.006	0.008	0.007	0.008		0.002	0.006	0.005	0.006	0.008	0.007	0.009
HSU	0.009	0.077	0.097	0.135	0.296	0.212	0.173		0.008	0.080	0.084	0.132	0.303	0.220	0.173
	0.002	0.007	0.006	0.006	0.008	0.008	0.012		0.001	0.007	0.005	0.006	0.008	0.008	0.011
HSG	0.006	0.057	0.079	0.119	0.288	0.232	0.219		0.004	0.052	0.062	0.109	0.289	0.246	0.237

	0.001	0.005	0.005	0.006	0.008	0.008	0.012		0.001	0.005	0.004	0.006	0.007	0.008	0.011
CU	0.002	0.031	0.052	0.088	0.256	0.254	0.317		0.002	0.035	0.047	0.089	0.267	0.260	0.300
	0.001	0.005	0.006	0.007	0.010	0.008	0.021		0.001	0.005	0.005	0.007	0.009	0.008	0.019
CG	0.001	0.019	0.036	0.067	0.224	0.257	0.396		0.001	0.017	0.027	0.059	0.218	0.264	0.415
	0.000	0.003	0.005	0.007	0.012	0.008	0.024		0.000	0.003	0.004	0.006	0.011	0.008	0.022
Nonpoor	0.013	0.092	0.102	0.130	0.265	0.191	0.207		0.012	0.094	0.085	0.123	0.198	0.223	0.223
	0.002	0.004	0.004	0.005	0.007	0.006	0.005		0.002	0.004	0.004	0.005	0.006	0.005	0.005
Poor	0.045	0.182	0.145	0.151	0.240	0.134	0.103		0.028	0.150	0.110	0.141	0.164	0.149	0.149
	0.006	0.012	0.007	0.006	0.008	0.008	0.010		0.005	0.012	0.007	0.006	0.008	0.013	0.013

Note: Values in each row are interpreted as the probabilities that the son will achieve a certain level of schooling with reference to a particular attribute of parents and household. For instance, the value associated with the cell formed by CG and Nonpoor (0.207) means that the probability that a son will finish a college degree is 20%, given that he comes from a nonpoor household in 2006.

Table A14 Estimated probabilities that a daughter will finish a certain level of education: 2006 and 2009

	Daughter's educational attainment:2006								Daughter's educational attainment:2009						
Father's Education	NGC	EU	EG	HU	HG	CU	CG		NGC	EU	EG	HU	HG	CU	CG
NGC	0.048	0.071	0.089	0.112	0.292	0.196	0.192		0.046	0.068	0.088	0.104	0.318	0.190	0.187
	0.013	0.014	0.013	0.012	0.011	0.015	0.035		0.012	0.013	0.013	0.011	0.011	0.015	0.035
EU	0.021	0.040	0.058	0.083	0.265	0.226	0.308		0.022	0.041	0.060	0.080	0.295	0.219	0.284
	0.003	0.004	0.005	0.006	0.011	0.008	0.017		0.003	0.004	0.005	0.006	0.011	0.008	0.017
EG	0.016	0.033	0.050	0.074	0.252	0.230	0.345		0.016	0.032	0.050	0.069	0.277	0.225	0.331
	0.003	0.004	0.005	0.006	0.010	0.008	0.016		0.003	0.004	0.005	0.005	0.010	0.008	0.016
HSU	0.012	0.026	0.042	0.065	0.235	0.231	0.389		0.012	0.025	0.041	0.060	0.258	0.227	0.376
	0.002	0.004	0.005	0.006	0.011	0.008	0.021		0.002	0.004	0.005	0.006	0.012	0.008	0.022
HSG	0.010	0.022	0.037	0.058	0.222	0.230	0.420		0.008	0.018	0.031	0.048	0.229	0.226	0.440
	0.002	0.003	0.004	0.005	0.010	0.008	0.017		0.002	0.003	0.004	0.004	0.010	0.008	0.017
CU	0.003	0.010	0.018	0.033	0.158	0.208	0.570		0.005	0.012	0.023	0.037	0.198	0.218	0.507
	0.001	0.002	0.003	0.004	0.012	0.009	0.025		0.001	0.002	0.003	0.004	0.012	0.008	0.024
CG	0.002	0.006	0.013	0.025	0.130	0.191	0.633		0.002	0.005	0.011	0.020	0.134	0.185	0.643
	0.001	0.002	0.003	0.004	0.014	0.011	0.031		0.001	0.001	0.002	0.004	0.015	0.011	0.030
Mother's Education															
NGC	0.052	0.075	0.094	0.116	0.296	0.192	0.175		0.049	0.071	0.090	0.106	0.319	0.187	0.177
	0.013	0.013	0.013	0.011	0.010	0.015	0.031		0.013	0.014	0.013	0.011	0.010	0.016	0.034
EU	0.022	0.041	0.060	0.085	0.271	0.227	0.293		0.022	0.040	0.059	0.078	0.292	0.220	0.290
	0.003	0.005	0.006	0.007	0.011	0.008	0.018		0.003	0.005	0.006	0.006	0.011	0.008	0.018
EG	0.015	0.031	0.048	0.073	0.252	0.233	0.347		0.016	0.032	0.049	0.068	0.275	0.225	0.335
	0.002	0.004	0.004	0.006	0.010	0.008	0.015		0.002	0.003	0.004	0.005	0.010	0.008	0.015
HSU	0.013	0.028	0.045	0.068	0.244	0.234	0.368		0.011	0.024	0.039	0.057	0.252	0.228	0.390
	0.003	0.004	0.005	0.006	0.011	0.008	0.021		0.002	0.003	0.004	0.005	0.011	0.008	0.021
HSG	0.008	0.018	0.032	0.052	0.210	0.231	0.449		0.010	0.022	0.037	0.054	0.245	0.227	0.405
	0.002	0.003	0.004	0.005	0.010	0.008	0.019		0.002	0.003	0.004	0.005	0.010	0.008	0.017

CU	0.005	0.013	0.023	0.041	0.181	0.222	0.515		0.005	0.012	0.023	0.037	0.196	0.217	0.511
	0.001	0.003	0.004	0.005	0.014	0.009	0.028		0.001	0.002	0.004	0.005	0.013	0.008	0.026
CG	0.001	0.004	0.010	0.019	0.109	0.176	0.680		0.002	0.005	0.010	0.019	0.127	0.180	0.658
	0.000	0.001	0.002	0.003	0.013	0.011	0.028		0.000	0.001	0.002	0.003	0.013	0.010	0.027
Nonpoor	0.014	0.029	0.043	0.064	0.220	0.210	0.420		0.014	0.028	0.043	0.059	0.239	0.205	0.412
	0.002	0.003	0.004	0.004	0.007	0.007	0.008		0.002	0.003	0.003	0.004	0.007	0.007	0.008
Poor	0.053	0.072	0.086	0.105	0.265	0.183	0.236		0.056	0.073	0.088	0.099	0.288	0.174	0.222
	0.010	0.010	0.009	0.009	0.009	0.009	0.024		0.010	0.010	0.009	0.008	0.009	0.009	0.022

Note: Values in each row are interpreted as the probabilities that a daughter will achieve a certain level of schooling with reference to a particular attribute of parents and household. For instance, the value associated with the cell formed by CG and Nonpoor (0.420) means that the probability that a daughter will finish a college degree is 42%, given that she comes from a nonpoor household in 2006.

Table A15 Marginal effects on educational outcomes: sons

	Son's educational attainment:2006								Son's educational attainment:2009						
Father's Education	NGC	EU	EG	HU	HG	CU	CG		NGC	EU	EG	HU	HG	CU	CG
EU	-0.014	-0.042	-0.021	-0.009	0.018	0.032	0.036		-0.020	-0.067	-0.027	-0.013	0.031	0.049	0.046
	0.016	0.007	0.019	0.009	0.003	0.010	0.014		0.014	0.009	0.024	0.008	0.002	0.014	0.013
EG	-0.019	-0.063	-0.034	-0.017	0.023	0.050	0.061		-0.026	-0.097	-0.043	-0.025	0.037	0.075	0.079
	0.017	0.007	0.020	0.009	0.003	0.010	0.015		0.015	0.009	0.025	0.009	0.003	0.014	0.014
HSU	-0.025	-0.092	-0.055	-0.033	0.023	0.076	0.107		-0.030	-0.116	-0.055	-0.036	0.036	0.093	0.108
	0.018	0.007	0.020	0.010	0.005	0.010	0.015		0.017	0.009	0.026	0.009	0.005	0.014	0.016
HSG	-0.028	-0.109	-0.070	-0.047	0.015	0.092	0.148		-0.033	-0.145	-0.076	-0.060	0.022	0.120	0.173
	0.018	0.007	0.020	0.010	0.006	0.010	0.015		0.018	0.009	0.025	0.010	0.006	0.014	0.017
CU	-0.031	-0.127	-0.088	-0.066	-0.002	0.107	0.207		-0.036	-0.169	-0.099	-0.089	-0.014	0.139	0.268
	0.018	0.007	0.020	0.011	0.008	0.012	0.016		0.024	0.009	0.025	0.010	0.007	0.016	0.022
CG	-0.033	-0.144	-0.109	-0.091	-0.035	0.115	0.296		-0.037	-0.184	-0.116	-0.117	-0.065	0.137	0.382
	0.017	0.007	0.020	0.011	0.009	0.015	0.015		0.030	0.009	0.025	0.010	0.008	0.018	0.029
Mother's Education															
EU	-0.014	-0.043	-0.020	-0.007	0.021	0.032	0.031		-0.003	-0.009	-0.004	-0.002	0.004	0.007	0.007
	0.015	0.007	0.019	0.008	0.002	0.011	0.013		0.012	0.006	0.021	0.009	0.004	0.009	0.015
EG	-0.024	-0.082	-0.045	-0.022	0.032	0.066	0.076		-0.015	-0.064	-0.032	-0.023	0.016	0.052	0.066
	0.016	0.007	0.019	0.009	0.003	0.011	0.014		0.013	0.006	0.021	0.009	0.005	0.009	0.016
HSU	-0.028	-0.101	-0.059	-0.033	0.031	0.083	0.106		-0.017	-0.077	-0.041	-0.031	0.014	0.064	0.087
	0.017	0.007	0.020	0.010	0.005	0.011	0.015		0.015	0.006	0.022	0.010	0.006	0.009	0.018
HSG	-0.031	-0.121	-0.077	-0.050	0.023	0.103	0.153		-0.021	-0.105	-0.062	-0.054	0.000	0.090	0.151
	0.017	0.007	0.020	0.010	0.005	0.011	0.015		0.017	0.006	0.021	0.010	0.007	0.009	0.019
CU	-0.035	-0.147	-0.105	-0.080	-0.008	0.125	0.251		-0.022	-0.123	-0.078	-0.074	-0.022	0.105	0.214
	0.017	0.007	0.020	0.011	0.008	0.013	0.015		0.025	0.006	0.022	0.011	0.009	0.012	0.025
CG	-0.036	-0.159	-0.120	-0.101	-0.040	0.128	0.329		-0.024	-0.141	-0.097	-0.104	-0.072	0.109	0.329
	0.016	0.007	0.020	0.011	0.009	0.015	0.014		0.029	0.006	0.021	0.011	0.009	0.014	0.029

Urbanity	0.010	0.033	0.021	0.014	0.000	-0.022	-0.056		0.002	0.008	0.004	0.004	0.001	-0.005	-0.014
	0.014	0.008	0.027	0.017	0.012	0.001	0.018		0.045	0.006	0.023	0.012	0.010	0.002	0.039
Age	0.001	0.003	0.002	0.001	0.000	-0.002	-0.005		-0.003	-0.011	-0.006	-0.005	-0.001	0.007	0.019
	0.002	0.001	0.003	0.002	0.001	0.000	0.002		0.005	0.001	0.003	0.002	0.001	0.000	0.005
Square of Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000
Remittances	-0.008	-0.027	-0.017	-0.012	0.000	0.018	0.045		-0.005	-0.019	-0.010	-0.008	-0.001	0.011	0.032
	0.002	0.001	0.003	0.002	0.001	0.001	0.002		0.005	0.001	0.003	0.001	0.001	0.001	0.004
Poverty status	0.032	0.090	0.044	0.021	-0.026	-0.058	-0.103		0.016	0.056	0.025	0.018	-0.007	-0.034	-0.074
	0.007	0.006	0.012	0.005	0.002	0.006	0.007		0.009	0.004	0.012	0.005	0.003	0.003	0.012

Note: Estimates represent effects of changes in key attributes on the probability that a son will finish a certain level of education. To arrive at estimates, an ordered probit model with the educational attainment of sons as a dependent variable is estimated. This is determined by parental education, regional and urbanity dummies, remittances from abroad and poverty status. To interpret, consider the cell formed by Poverty status and CG. The estimate, - 0. 103 represents the change in probability that a son will graduate from college when poverty status of household changes from Non – poor to Poor. So, with the estimate, we say that the change in probability that a son will graduate from college has decreased by 10 percentage points.

Table A16 Marginal effects on educational outcomes: Daughters

	Daughter's educational attainment:2006								Daughter's educational attainment:2009						
Father's Education	NGC	EU	EG	HU	HG	CU	CG		NGC	EU	EG	HU	HG	CU	CG
EU	0.415	-0.027	-0.031	-0.029	-0.027	0.030	0.115		-0.023	-0.027	-0.028	-0.025	-0.024	0.029	0.098
	0.141	0.012	0.013	0.009	0.005	0.014	0.035		0.012	0.012	0.012	0.009	0.006	0.014	0.034
EG	0.532	-0.032	-0.038	-0.038	-0.040	0.034	0.153		-0.029	-0.036	-0.038	-0.035	-0.041	0.035	0.144
	0.147	0.012	0.013	0.010	0.006	0.014	0.037		0.012	0.013	0.012	0.010	0.007	0.015	0.037
HSU	0.663	-0.036	-0.045	-0.047	-0.057	0.035	0.196		-0.034	-0.042	-0.046	-0.044	-0.060	0.038	0.189
	0.154	0.013	0.013	0.011	0.009	0.014	0.040		0.012	0.013	0.013	0.011	0.010	0.015	0.040
HSG	0.755	-0.038	-0.049	-0.054	-0.070	0.035	0.228		-0.038	-0.050	-0.056	-0.056	-0.089	0.036	0.253
	0.152	0.013	0.013	0.011	0.009	0.014	0.039		0.012	0.013	0.013	0.011	0.010	0.015	0.039
CU	1.178	-0.045	-0.061	-0.079	-0.134	0.012	0.377		-0.041	-0.055	-0.065	-0.067	-0.121	0.028	0.320
	0.163	0.013	0.014	0.012	0.014	0.015	0.045		0.012	0.013	0.013	0.011	0.014	0.015	0.044
CG	1.363	-0.046	-0.065	-0.087	-0.162	-0.005	0.441		-0.044	-0.063	-0.076	-0.084	-0.185	-0.005	0.456
	0.174	0.013	0.014	0.012	0.017	0.017	0.050		0.012	0.013	0.013	0.012	0.018	0.017	0.049
Mother's Education															
EU	0.432	-0.030	-0.034	-0.031	-0.025	0.035	0.118		-0.028	-0.031	-0.032	-0.028	-0.027	0.033	0.112
	0.132	0.012	0.012	0.009	0.005	0.014	0.032		0.012	0.013	0.012	0.009	0.006	0.015	0.034
EG	0.602	-0.036	-0.044	-0.043	-0.044	0.041	0.172		-0.033	-0.040	-0.041	-0.038	-0.044	0.039	0.157
	0.136	0.012	0.013	0.009	0.006	0.015	0.033		0.013	0.013	0.012	0.010	0.006	0.015	0.035
HSU	0.663	-0.038	-0.047	-0.048	-0.052	0.042	0.193		-0.038	-0.047	-0.051	-0.049	-0.067	0.041	0.212
	0.145	0.012	0.013	0.010	0.008	0.015	0.037		0.013	0.013	0.013	0.010	0.010	0.015	0.039
HSG	0.895	-0.044	-0.057	-0.064	-0.086	0.039	0.274		-0.039	-0.049	-0.054	-0.052	-0.074	0.041	0.228
	0.145	0.012	0.013	0.011	0.010	0.015	0.038		0.013	0.014	0.013	0.011	0.010	0.015	0.039
CU	1.079	-0.047	-0.063	-0.075	-0.115	0.030	0.340		-0.044	-0.059	-0.068	-0.069	-0.123	0.030	0.334
	0.157	0.013	0.013	0.011	0.015	0.015	0.044		0.013	0.014	0.013	0.011	0.015	0.015	0.045
CG	1.557	-0.050	-0.071	-0.097	-0.187	-0.016	0.505		-0.048	-0.066	-0.080	-0.087	-0.192	-0.007	0.481
	0.162	0.013	0.013	0.011	0.016	0.017	0.045		0.013	0.014	0.013	0.011	0.017	0.017	0.046

Urbanity	-0.010	-0.013	-0.015	-0.016	-0.028	0.000	0.081		-0.008	-0.010	-0.012	-0.012	-0.025	0.001	0.066
	0.010	0.013	0.015	0.017	0.029	0.001	0.084		0.011	0.013	0.016	0.016	0.033	0.002	0.087
Age	0.000	0.000	0.000	0.000	0.001	0.000	-0.002		0.001	0.001	0.001	0.001	0.002	0.000	-0.006
	0.001	0.001	0.002	0.002	0.003	0.000	0.009		0.001	0.001	0.001	0.002	0.003	0.000	0.008
Square of Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000
Remittances	-0.004	-0.005	-0.006	-0.006	-0.011	0.000	0.031		-0.004	-0.005	-0.006	-0.006	-0.012	0.001	0.033
	0.001	0.001	0.001	0.001	0.002	0.000	0.007		0.001	0.001	0.001	0.001	0.003	0.000	0.007
Poverty status	0.039	0.044	0.043	0.040	0.045	-0.027	-0.184		0.042	0.045	0.045	0.040	0.049	-0.031	-0.190
	0.009	0.009	0.008	0.006	0.004	0.007	0.024		0.009	0.009	0.007	0.006	0.004	0.008	0.022

Note: Estimates represent effects of changes in key attributes on the probability that a daughter will finish a certain level of education. To arrive at estimates, an ordered probit model with the educational attainment of daughters as a dependent variable is estimated. This is determined by parental education, regional and urbanity dummies, remittances from abroad and poverty status. To interpret, consider the cell formed by Poverty status and CG. The estimate, - 0. 184 represents the change in probability that a daughter will graduate from college when poverty status of household changes from Non – poor to Poor. So, with the estimate, we say that the change in probability that a daughter will graduate from college has decreased by 18 percentage points.

Table A17 Ordered probit estimates for parental education parameters

	Sons			Daughters	
	2006	2009		2006	2009
Father's education					
EU	0.247	0.357		0.415	0.360
	0.105	0.119		0.141	0.141
EG	0.385	0.544		0.532	0.509
	0.110	0.124		0.147	0.148
HSU	0.604	0.686		0.663	0.644
	0.115	0.129		0.154	0.155
HSG	0.768	0.949		0.755	0.829
	0.116	0.128		0.152	0.152
CU	0.981	1.271		1.178	1.016
	0.127	0.135		0.163	0.160
CG	1.262	1.609		1.363	1.405
	0.133	0.143		0.174	0.172
Mother's education					
EU	0.236	0.051		0.432	0.416
	0.100	0.112		0.132	0.141
EG	0.493	0.391		0.602	0.557
	0.102	0.114		0.136	0.146
HSU	0.637	0.490		0.663	0.721
	0.109	0.120		0.145	0.154
HSG	0.826	0.750		0.895	0.766
	0.110	0.121		0.145	0.154
CU	1.163	0.970		1.079	1.065
	0.123	0.130		0.157	0.164
CG	1.400	1.321		1.557	1.489
	0.126	0.133		0.162	0.169

Note: The table only includes a subset of parameters pertaining to parental education. Parameter estimates (in black) and standard error (in red) were arrived at using the ordered probit model. The estimates are expressed in nominal terms and not interpreted as probabilities. They confirm the numerical superiority of estimates associated with CG.

Table A18 Selected parameter estimates from selectivity models: Daughters

	2006						2009				
	Model 1	Model 2	Model 3	Model 4	Model 5		Model 1	Model 2	Model 3	Model 4	Model 5
Own education											
EUG	-0.781						0.313				
	0.218						0.441				
EG	-1.251						-0.142				
	0.148						0.445				
HSUG	-1.071						-0.029				
	0.150						0.425				
HSG	-0.797						0.359				
	0.092						0.415				
CUG	-0.572						0.595				
	0.088						0.415				
CG	-						1.283				
	(omitted)						0.427				
Father's log wage		0.565						0.378			
		0.059						0.050			
Father's predicted log wage			0.853						0.680		
			0.089						0.083		
Father's education											
EUG				0.575	0.672					0.199	0.011
				0.182	0.194					0.191	0.207
EG				0.607	0.714					0.283	0.076
				0.184	0.201					0.192	0.211
HSUG				0.669	0.769					0.427	0.167
				0.188	0.204					0.198	0.218
HSG				0.763	0.816					0.423	0.168
				0.184	0.202					0.192	0.213
CUG				0.941	0.933					0.564	0.253
				0.188	0.207					0.195	0.217
CG				1.193	1.113					0.791	0.423
				0.188	0.210					0.195	0.219
Mother's education											
EUG					-0.381						0.345
					0.190						0.210

EG					-0.428						0.281
					0.190						0.209
HSUG					-0.400						0.432
					0.197						0.216
HSG					-0.350						0.378
					0.194						0.215
CUG					-0.257						0.435
					0.199						0.220
CG					-0.156						0.525
					0.197						0.219
Permanent status					0.128						0.230
					0.050						0.052
Inverse of Mill's ratio	0.016	-0.223	-0.137	-0.817	-0.761		0.219	-0.637	-0.509	-0.767	-0.681
	0.135	0.106	0.107	0.082	0.081		0.113	0.129	0.123	0.080	0.079
Mean of Inverse Mills Ratio	1.208	2.101	2.101	1.208	1.208		1.165	2.220	2.220	1.165	1.165
Truncation effect	0.020	-0.469	-0.288	-0.986	-0.919		0.255	-1.414	-1.131	-0.894	-0.793

Notes: All wage outcome models control for demographic characteristics, regional residence, and urbanity. For selection equations, demographic characteristics, urbanity, regional residence, household composition variables, educational dummies, and nonlabor income. Essentially, differences exist among wage equation variants. Model 1 uses a son's own educational attainment. Model 2 uses father's wages and no educational dummies are included. Model 3 uses father's predicted wages using occupational and educational dummies. Model 4 includes father's educational achievements and model 5 incorporates parental educational achievements and a dummy for permanent job status.

Table A19 Selected parameter estimates from selectivity models: Sons

	2006						2009				
	Model 1	Model 2	Model 3	Model 4	Model 5		Model 1	Model 2	Model 3	Model 4	Model 5
Own education											
EUG	-0.112						-0.580				
	0.188						0.430				
EG	0.121						-0.516				
	0.188						0.447				
HSUG	0.051						-0.546				
	0.185						0.435				
HSG	0.176						-0.418				
	0.185						0.453				
CUG	0.300						-0.261				
	0.184						0.416				
CG	0.721						0.166				
	0.190						0.487				
Father's log wage		0.380						0.394			
		0.035						0.033			
Father's predicted log wage			0.592						0.631		
			0.054						0.046		
Father's education											
EUG				0.129	0.123					0.006	-0.004
				0.111	0.114					0.207	0.196
EG				0.100	0.071					0.057	0.031
				0.112	0.117					0.210	0.201
HSUG				0.233	0.215					0.140	0.078
				0.114	0.118					0.218	0.207
HSG				0.271	0.205					0.185	0.069
				0.113	0.120					0.213	0.204
CUG				0.450	0.322					0.335	0.170
				0.118	0.126					0.220	0.211
CG				0.730	0.533					0.544	0.311
				0.118	0.129					0.223	0.216
Mother's education											
EUG					-0.051						0.033

					0.111						0.204
EG					0.005						0.069
					0.111						0.207
HSUG					-0.034						0.087
					0.114						0.211
HSG					0.026						0.190
					0.115						0.210
CUG					0.118						0.243
					0.122						0.220
CG					0.221						0.326
					0.123						0.218
Permanent status					0.083						0.132
					0.030						0.043
Inverse of Mill's ratio	0.289	0.027	0.053	-0.425	-0.348		-0.296	-0.227	-0.198	-1.496	-1.287
	0.120	0.108	0.108	0.108	0.106		0.382	0.083	0.080	0.309	0.271
Mean of Inverse of Mill's ratio	1.066	1.714	1.714	1.066	1.066		1.006	1.717	1.717	1.006	1.006
Truncation effect	0.309	0.046	0.090	-0.453	-0.371		-0.298	-0.389	-0.340	-1.505	-1.294

Notes: All wage outcome models control for demographic characteristics, regional residence, and urbanity. For selection equations, demographic characteristics, urbanity, regional residence, household composition variables, educational dummies, and nonlabor income. Essentially, differences exist among wage equation variants. Model 1 uses a son's own educational attainment. Model 2 uses father's wages and no educational dummies are included. Model 3 uses father's predicted wages using occupational and educational dummies. Model 4 includes father's educational achievements and model 5 incorporates parental educational achievements and a dummy for permanent job status.