Decomposing Intergenerational Income Elasticity: The gender-differentiated contribution of capital transmission in rural Philippines

Leah Bevis and Christopher B. Barrett
Cornell University

April 2013 revision
Comments greatly appreciated

Abstract
A growing empirical literature documents strong intergenerational income elasticity (IGE) worldwide while a parallel literature finds clear patterns of parent-to-child transmission of human capital. Although the latter pattern clearly helps explain the IGE, this paper appears to be the first attempt to decompose the IGE into different pathways of intergenerational capital and productivity transmission. Using longitudinal data from rural Philippines, we decompose IGE into five distinct pathways: the intergenerational transmissions of health, education, land, and spouse capital, plus intergenerational correlation in productivity. We find that intergenerational human capital transmissions from mothers are stronger than those from fathers. Although the naïve IGE estimates are statistically indistinguishable for sons and daughters, the pathways that generate these results differ strikingly. For sons, IGE is entirely explained by parent-to-child capital transmission. By contrast, strong income correlation exists between daughters and parents even after controlling for parent and child capital, indicating strong productivity transmission to daughters independent of asset endowments. These results suggest that it may be easier to promote equality of opportunity among males than among females in rural Philippines.

Acknowledgements
We thank the NSF-funded Food Systems and Poverty Reduction IGERT for financial support, IFPRI for making the data available, Ravi Kanbur and Jordan Matsudaira for their feedback and suggestions, and workshop audiences at Columbia, Cornell, and the 2013 Oxford CSAE conference for helpful comments and questions. Special thanks go to Kazushi Takahashi, Agnes Quisumbing, Catherine Porter and Sonia Bhalotra for their comments and suggestions on an earlier draft of this paper. Any remaining errors are our sole responsibility.

1. Introduction

Intergenerational income transmission estimates measure a crucial characteristic of a society: equality of opportunity. Are all children equally likely to forge a successful (or unsuccessful) future livelihood – as reflected by zero correlation between parents' and children's incomes – or are children destined to stand upon the same socio-economic rungs as their parents, as would be true if incomes were perfectly correlated intergenerationally? And if a child's income is highly correlated with his or her parents', through which mechanism(s) does this transmission occur? Do the parents' productive assets pass to the children, and if so, is it human capital embodied in education and/or health, or is it financial or physical capital, such as agricultural land? Or is it instead the productivity with which parents and children employ their wealth, perhaps due to skill or social connections, such as socioeconomic matching in marriage? And are patterns of intergenerational transmission gender neutral or do mothers and fathers exert identifiably different effects on their children's adult well-being, and do daughters and sons depend differentially on parents for their own adult incomes? We know surprisingly little empirically about these more nuanced questions about the underlying structure behind oft-observed intergenerational income correlations that suggest limited equality of opportunity.

That lacuna matters. Understanding the pathways that tie children's economic outcomes to those of their parents allows policymakers to craft policies that work towards providing all children with equal opportunities in life. Research on the topic gains particular pertinence, therefore, in the developing world, where evidence suggests that intergenerational income transmission may be especially high (Solon 2002), and where the effective targeting of costly policies is crucial to success in poverty reduction.

Most economists couch parent-to-child income transmission in terms of intergenerational income elasticity (IGE) estimates generated through regression of children's adult log income on their parents' log income. In equation 1, the log income of parents in household *j* is given by y_j, the log income of child *i* in household *j* is given by y_{ij}, and IGE is given by the estimated coefficient b_1:

$$y_{ij} = b_0 + b_1 y_j + e \qquad (1)$$

While IGE is an interesting descriptive measure, it obviously describes only statistical correlation; it does not illuminate the pathways between parent and child income. And many potential pathways exist. Understanding their relative importance is crucial to the design of policies designed to reduce intergenerational income transmission so as to enhance equality of opportunity. For instance, perhaps wealthier parents invest more in (better) education for their children, and a positive return to education raises these children's adult incomes relative to those of children of poorer parents. Or perhaps wealthier parents transfer (inter vivos or via inheritance) land, money or other physical assets to their children, and this greater wealth leads directly to higher adult incomes for these children. In the first scenario better quality, free education might level the playing field among children born into households of different economic status, while in the second scenario a more progressive tax system or land redistribution policy may be appropriate.

Or perhaps there is no appreciable difference in education or productive asset holdings by the children of higher income households, and the adult incomes of the children of wealthier parents are greater only because of their superior productivity, which is correlated across generations due to differences in genetics, transferable skills, greater financial liquidity, or social connections. In such a case, where IGE arises due to intrinsic heterogeneity that is correlated within families, there may not be a policy option for further increasing equality of opportunity.

We can couch most intergenerational income pathways in terms of intergenerational transmissions of productive capital such as education, health, or land. Assortative marriage might be viewed as a fourth pathway, if parents exert any influence over marriage patterns and couples pool incomes at all. Controlling for these four pathways, any residual IGE conditional on parent capital and spousal characteristics would signal intergenerational correlation in productivity independent of human, physical or marital capital access.

Note that intergenerational capital transmissions are, like IGE, a statistical measure of correlation. Knowing that parent health or landholdings are correlated with child health or landholdings does not make clear the structural mechanism that underpins these transmissions. Nonetheless, decomposing IGE estimates into component pathways can enhance our understanding of intergenerational income transmission, if only by narrowing down the candidate mechanisms to explore for policy purposes.

While IGE and international capital transmissions have each been well documented within their own literatures (see section 2, below), few studies have attempted to decompose IGE into the constituent capital transmissions behind it. Those authors who do attempt decomposition focus only on one mechanism, generating estimates that may be biased by unobserved but correlated pathways (Eriksson et al 2005, Piraino 2007). To our knowledge, decomposition of IGE into multiple pathways has not yet been attempted. We attempt it in this paper, conceptualizing IGE in Bukidnon, Philippines, as the result of intergenerational transmission of four different types of capital – education, health, land, and spouse education – and any remaining, conditional IGE due to intergenerational correlation in productivity.

In order to understand the contribution of intergenerational capital transmission to IGE, we first examine each transmission pathway in turn. We explore the association between parent capital levels and child capital levels, allowing for cross-capital transmission such as the relationship between parent education and child health. We briefly consider potential mechanisms behind these capital transmission patterns, such as child feeding practices. We then decompose IGE into parent capital transmissions and parent income transmission. We estimate all results separately for males and females, and some results separately for migrants and non-migrants ("splits"), while controlling for measurement error and life cycle effects that otherwise bias IGE estimates downwards (Black & Devereux 2010).

The rest of this paper proceeds as follows. Section 2 provides background through a brief literature review. Section 3 develops a simple conceptual model for intergenerational income transmission, and uses this model to derive reduced form equations for

intergeneration capital and income transmission. Section 4 describes the Philippine data used in this paper. Section 5 explains the estimation strategy used. Section 6 presents the results for the capital and income transmission equations. Section 7 concludes.

2. Background

Methods of estimating intergenerational income elasticity have improved over time. Older studies of IGE in the United States (US) typically found IGE estimates of 0.2 or less (Solon 2002), signaling considerable equality of opportunity. Such findings, however, were usually biased by measurement error and lifecycle effects (Behrman & Taubman 1990, Solon 2002). Correcting for measurement error and lifecycle effects using average parent income across multiple years commonly increases IGE estimates to around 0.4 in the United Kingdom (UK) and US (Solon 2002), with lower estimates of around 0.1 – 0.2 in Canada and the Nordic countries of Europe (Corak & Heisz 1999, Österbacka 2001, Solon 2002).

It is possible, however, that most existing studies still under-estimate IGE due to the effects of transitory income and price shocks. Such transitory shocks may be viewed as measurement error around structural income, where structural income is defined as asset-driven permanent income that can be changed only by an alteration in asset holdings or in the return to assets (Naschold & Barrett 2011). Unlike classical measurement error, error due to transitory shocks is likely to persist across time, and longer panels are thus required to mitigate the resulting attenuation bias on estimated income coefficients (Mazumder 2005, Naschold & Barrett 2011). Mazumder (2005) shows that IGE estimates rose from 0.45 when averaging across 7 years of US social security data to 0.61 when averaging across 16 years.

Studies of intergenerational income transmission have generally focused on a particular demographic: males in the developed world. The lack of studies in poorer countries is largely due to lack of reliable income data (Núñez & Miranda 2011, Black & Devereux 2010). However, the few studies that have investigated income transmission in poor countries usually find comparably high IGE rates (Solon 2002). Conversely, the few studies which have investigated parent to daughter IGE – in the developed world – have found comparably lower IGE rates for daughters than for sons (Chadwick & Solon 2002, Jäntti et al 2005). Raaum et al (2008) provide a framework for understanding how IGE differs across sons and daughters, and attribute much of the difference to assortative marriage and labor supply responses.

Once estimated, the crucial question is what generates these IGEs. A large body of economics research from the 1990s suggests that educational achievement is correlated within families and across generations (Thomas 1996, Behrman 1997, Behrman et al 2001). A second body of the economics and nutrition literatures explores how parent education and parent health each influence the health outcomes of children (Thomas et al 1991, Thomas 1994, Bhalotra & Rawlings 2011, forthcoming). Given the income returns to both health and education, these intergenerational human capital transmissions seem likely to play an important role underpinning IGE (Alburg 1998).

Similar to the method used in estimating IGE, economists often couch education transmission in terms of an estimated regression coefficient. In the United States, for example, Behrman and Rosenzweig (2002) found median estimates of 0.12 years and 0.15 years of child schooling for every additional year of mother's and father's schooling, respectively. Behrman and Rosenzweig (2002) found intergenerational education correlations of 0.5-0.7 in Latin America, and Thomas (1996) found correlations of 0.2-0.4 in South Africa, depending on race and parent gender. Relatively high rates of intergenerational schooling transmission in poorer countries may be due low levels of parent education, poor macroeconomic conditions and to a lack of government investment in public education, all found to be significantly related to low levels of schooling mobility (Behrman & Rosenzweig 2002, Corak & Heisz 1999, Hertz et al 2007).

Health transmission is more difficult to estimate than education transmission, given the multidimensional nature of health (Strauss & Thomas 1998). Estimates of parent-child lifespan correlation fall between 0.15 and 0.3 (Yashin & Iachine 1997). Eriksson et al (2005) find an average parent-child morbidity correlation of a bit under 0.3. Mother's birth weight and nutritional status is clearly associated with child birth weight (Currie & Moretti 2007, Victoria et al 2008, Black et al 2008), and Bhalotra and Rawlings (2011) find positive associations between maternal and child health over a range of indicators in 38 developing countries. Height is often considered the best single measure of adult health "stock," given that it captures health shocks from in utero through early adulthood (Thomas et al 1991, Thomas 1994). In the developing world especially, where stunting due to malnutrition and disease is widespread, height may be the most telling measure of accumulated health (Fogel 2004, Costa 1998, Dasgupta 1997).

Cross-capital transmission between education and health is also well documented, the most common example being the impact of maternal education on child health. Thomas et al (1991) find that maternal education predicts child height-for-age, and that this association appears to be working through access to information. Thomas (1994) finds that in three countries (Brazil, Ghana and the US) maternal education has a larger positive impact on daughters' height than sons' height, while the opposite is true for paternal education.

Given the well-established literature on international transmission of education and health, it is surprising that only a few studies have attempted to estimate the contribution of either transmission to IGE. Piraino (2007) estimates that intergenerational education transmission accounts for roughly one-third of IGE in Italy. Pekkarinen et al (2009) find that major educational reform in Finland reduced IGE by 23 percent, and Asadullah (2012) finds that controlling for son's education reduces estimated IGE in rural Bangladesh. Eriksson et al (2005) find that after controlling for child health status, estimated IGE in Denmark drops by 28 percent for sons and by 25 percent for daughters.

To our knowledge, only one paper attempts to simultaneously account for multiple intergenerational transmission pathways behind IGE. Blanden et al (2013) use a decomposition approach to investigate the contribution of education, occupation, labor

market attachment, marital status and health to IGE for male children in the US and Great Britain. They find that education transmission is the predominant pathway behind IGE in the US, while occupation transmission is the predominant pathway behind IGE in Great Britain. Their study illustrates the variable importance of transmission pathways behind IGE even within culturally similar, developed countries and for children of a single gender. It thus highlights the need for greater investigation of these pathways in other contexts.

Given the importance of land in agrarian societies, it seems likely that land inheritance may also play a role in creating intergenerational income correlations in much of the developing world. For instance, a significant proportion of children in the rural Philippines inherit land upon marriage or a parent's death, though this practice is declining as land becomes scarcer (Estudillo et al 2001b). It seems clear that parents favor sons over daughters when bequeathing land to progeny, but in recent years favor daughters over sons when investing in education (Estudillo et al 2001a, Estudillo et al 2001b). Estudillo et al (2001a) attribute the land inheritance pattern to the fact that in their study area land is primarily used for rice cultivation, traditionally a male domain.

Recently, a number of scholars have shown that assortative marriage contributes significantly to intergenerational income elasticity (Raaum et al 2008, Black & Devereux 2010). Chadwick and Solon (2002) find that in the US (where spouses typically have separate incomes), the individual earnings of a husband or wife are as highly correlated with the earnings of his or her in-laws as with the earnings of his or her parents. Ermisch et al (2006) estimate that about 40 percent of family income persistence in the UK and in Germany results from assortative marriage.

It seems possible that the effects of assortative marriage may be particularly important in the Philippines, where various authors agree that the returns to schooling are higher for women than for men (Sakellariou 2004, Quisumbing et al 2004). This may be in part because schooling increases labor force participation for women more than for men in the Philippines, or because of a relatively large gender earnings gap in favor of men within poorly educated subpopulations, which narrows quickly within more educated subpopulations (DeSilva & Bakhtiar 2011, Sakellariou 2004). DeSilva and Bakhtiar (2011) specify two additional avenues that they believe work through the marriage market. First, better educated women secure for themselves higher-earning husbands. Second, well-educated wives enhance the labor productivity of their husbands through the exchange of ideas, mutual learning, and intra-household specialization.

The narrative of migration has historically been one of upward economic mobility on the individual level. In both the Lewis (1954) and Harris-Todaro (1970) models, a gap between rural and expected urban earnings drives an individual to migrate. It is worth asking, however, how migration affects intergenerational economic mobility, if at all. Is migration an escape from the socio-economic circumstances of one's family, or does family income and productive capital pave the road for migrants, such that migration is simply another mechanism behind intergenerational income correlation?

Beegle et al (2011) find high income returns to migration from rural Tanzania; yet individuals who migrate usually come from better off families. This suggests that migration may work as a mechanism behind IGE in rural Tanzania. Quisumbing and McNiven (2010) suggest that migration may be used as an escape from family poverty in rural Philippines, but they also find that education increases one's likelihood of migrating. If there is intergenerational transmission of education, then it is unclear whether migration increases or decreases the association between migrant and parent income in this context. Adding to that ambiguity is the fact that Philippine migrants, especially daughters, commonly send remittances home to their families, which may increase parent-child income correlation in the "opposite" direction from that usually supposed.

In summary, it is clear that education, health, land, and the social capital of one's spouse are important predictors of income, both generally in the developing world and specifically in the Philippines (Maluccio et al 2009, Estudillo et al 2001a, Estudillo et al 2001b, Quisumbing 1994). These capital levels are influenced by parent capital, both directly and through parent income that can foster investment in children's capital accumulation. Such influence may differ across child and parent gender and also across space, as some children move further from their parents than others. Multivariate capital transmission therefore likely explains at least part of intergenerational income elasticity, although there may be residual IGE conditional on all of these factors, which would seem to reflect intergenerational correlation in productivity due to factors other than the controlled-for capital stocks. Moreover, how *much* each transmission pathway contributes to aggregate IGE, and whether the powers of various pathways differ across categories of children (male vs. female, or migrant vs. non-migrant), is an open question, unexplored in both the intergenerational income transmission literature and the intergenerational capital transmission literature. We contribute new findings to help begin to fill that gap.

3. Conceptual Model

In order to inform the empirical analysis that is the core contribution of this paper, in this section we lay out a simple, conceptual model of intergenerational transmission of different forms of capital that result in intergenerational correlation in incomes. Consider a household made up of parents and children. Following an approach begun by Becker (1974) and Becker and Tomes (1979), we assume parents are altruistic, and collectively maximize utility over current consumption and the expected future income levels of their children, constrained by their own current income. Child gender is exogenous, and parents perceive the future incomes of their children to be gender-specific functions of child education, health, land ownership, and the earning potential of the child's future spouse. Future income may also depend on children's attributes such as ability and social networks, observed by the parents but unobserved by the econometrician.

Parents maximize utility over current household consumption and child future income by choosing optimal levels of investment in child capital stocks, which generates intergenerational education transmission, health transmission, land transmission, and

spouse capital transmission to each of their children.[1] The first two pathways for human capital transmission occur during a child's formative years at home; the latter two usually occur when a child leaves his or her parent's house.[2] We assume that the decision to leave the house is exogenous to child characteristics, since most children eventually establish their own household. However, we allow a child's decision to migrate (rather than to remain in the local area of his or her birth) to be endogenous to parent and child capital levels. Parent income, which constrains the maximization problem, is itself a function of the same parent capital levels that contribute to child income: education, health, and land/asset ownership. Household size also constrains the maximization problem, and may also be a function of parent capital levels, such as maternal education.

Thus, intergenerational capital transmissions are affected by parent capital stocks in (at least) three distinct ways. First, transmissions are constrained directly by parent capital (e.g., an unhealthy mother will transmit poor health to her newborn, *ceteris paribus*). Second, intergenerational capital transmission is constrained by the effect of parent capital on parent income (e.g., poorly educated parents typically earn a low income limiting their ability to pay for schooling or health care for their children). Third, parental preferences and expectations may themselves be affected by parent capital (e.g., a poorly educated father may not believe that education is important to the future earnings of his children and might not put intrinsic value on their education).

The first and the third mechanisms will influence child capital levels regardless of parent income. The second mechanism reflects only the influence of parent capital on parent income, and the subsequent influence of parent income on child capital formation when liquidity constraints bind (Loury 1981). Of course, if parent income has little impact on child capital levels (in a society with high quality public schools and free government clinics, for instance, or with perfect long-term credit markets), this second mechanism may be weak. Moreover, intergenerational correlation in productivity can lead to intergenerational correlation in incomes independent of asset accumulation. So parental income can influence child adult income through any of several pathways, some direct and others indirect.

Parent perceptions may also depend upon child gender. For instance, parents may perceive the returns to land or education to differ across child gender, as found in the Philippines by Estudillo et al (2001a). Parent perceptions may also be shaped by social norms, which often regard birth order and may be dictated by ethnic group (La Ferrara 2007). It is therefore important to control for these factors when attempting to recover parent-to-child capital transmissions.

---

[1] Spouse capital transmission refers to the influence parents have over determining their child's future spouse. Parents may raise their child to prefer a certain type of spouse, they may directly choose their child's spouse, they may provide children with social networks which lead to a particular type of spouse, etc.

[2] In the BPS data, 73% of married children left the household the year they got married, and 84% left within 2 years of getting married. Of the 89 children who inherited land from their parents, 60% inherited within a year of leaving their parent's house, and 71% inherited within a year of getting married.

According to this framework, a child's adult income may be correlated with parent income through any of multiple mechanisms, some of which operate through parent income, others of which depend on parent capital levels independent of parental income. This stands in contrast to the workhorse regression specification for estimating IGE, equation 1, which ignores the influence of parent capital levels on child income.

To illustrate the value of decomposing IGE, consider the following, simplified version of the conceptual model laid out above. Parent *j*'s income relies on only one type of capital, education. The education of child *i* in household *j* is impacted by parent education (following pathways 1 and 3, above) and parent income (pathway 2). The child's adult income is a product of child capital and potentially of inherited productivity differences and/or the effects of omitted forms of intergenerationally transmitted capital (such as social connections), both of which may be correlated with parent income These conditions are given in equations 2-4, with parent income reflecting productivity conditional on capital in equation 4.

$$y_j = \alpha_o + \alpha_1 E_j + e_j \quad (2)$$
$$E_{ij} = \gamma_o + \gamma_1 E_j + \gamma_2 y_j + u_{ij} \quad (3)$$
$$y_{ij} = \delta_o + \delta_1 E_{ij} + \delta_2 y_j + v_{ij} \quad (4)$$

Substituting equation 3 into equation 4 gives a reduced form equation for child income, as in equation 5, which can be rewritten as equation 6. Additionally controlling for child capital results in equation 7, which enables us to isolate the intergenerational correlation in productivity independent of intergenerational transmission of capital.

$$y_{ij} = (\delta_o + \delta_1 * \gamma_o) + (\delta_1 * \gamma_1)E_j + (\delta_1 * \gamma_2 + \delta_2)y_j + (v_{ij} + \delta_1 * u_{ij}) \quad (5)$$
$$y_{ij} = \beta_o + \beta_1 E_j + \beta_2 y_j + w_{ij} \quad (6)$$
$$y_{ij} = \theta_o + \theta_1 E_j + \theta_2 y_j + \theta_3 E_{ij} + \varphi_{ij} \quad (7)$$

Equations 3, 4, 6 and 7 are the reduced form equations of interest. Equation 3 estimates the direct influence of parent education on child education, γ_1, and also the influence of parent education that works through parent income, γ_2. Equation 6 similarly estimates the direct influence of parent education on child income, β_1, and also the influence of parent income that works through both the effects of parental liquidity on child educational attainment and intergenerational correlation in productivity, β_2. The coefficient β_1 represents direct parent-to-child education transmission independent of parent income, γ_1, weighted by the influence of child education on child income, δ_1. The coefficient β_2 represents the parent-to-child education transmission that occurs only through the avenue of parent income, γ_2, weighted by the influence of child education on child income, δ_1, plus the intergenerational correlation of income conditional on child education, δ_2.

Equation 4 explains child adult income as a function of child educational attainment and parental income. This captures the effect of parental income, δ_2, that operates other than through investment in the child's productive capital. By controlling for both parental and child education, equation 7 isolates more cleanly the intergenerational productivity

transmission component of the IGE. If parent education influences child income only through the relations reflected in equations 2 and 3, then θ_1 should equal zero, indicating that parent education has no independent effect on child earnings other than its indirect effect through child education and parental income. Of course, then equation 7 collapses back to equation 4, yielding the testable hypotheses that $\theta_2 = \delta_2$ (the productivity transmission parameter) and $\theta_3 = \delta_1$ (the returns to education parameter).

This exploration of the pathways underscores that by regressing child income on parent income only, as in equation 1, one recovers the IGE 'naïve' estimate given in equation 8, which equals $\theta_2$from equation 7 plus the "bias" associated with the omission of parent and child education:

$$\text{IGE} \equiv b_1 = \theta_2 + \theta_1 Cov(E_j, y_j)/Var(y_j) + \theta_3 Cov(E_{ij}, y_j)/Var(y_j) \quad (8)$$

The naïve IGE estimate conflates the influence of parent income (or parent capital working through parent income) on child income directly, what we term 'productivity transmission', with the influence of parent education on child education or of parental income on child education and ultimately on child income through either pathway. Under the reasonably safe assumption that education and income are positively correlated, the more restrictive specification naturally leads to overstatement of the IGE that is attributable to income, and thus to intergenerational correlation in productivity, rather than to the intergenerational transmission of productive capital. This matters because the larger the share of the naïve estimate of IGE attributable to intergenerational transmission of capital, the greater the potential of public policy to enhance equality of opportunity by finding mechanisms to enhance children's access to capital independent of parents' income. If IGE is due primarily to productivity transmission, the policy levers available to promote equality of opportunity may be very limited indeed.

This simple example provides an intuition for the somewhat more complex conceptual model articulated above, which includes four types of capital rather than just one, and two periods of transmission. But the intuition remains similar. In the larger model, we can again gauge the direct influence of parent capital on child capital and thereby indirectly on child income through the coefficients on parent capital variables. The coefficients on parent income, however, estimate the joint influence of all parent capital levels working through their effect on parent income as well as the direct intergenerational elasticity of income due to correlated productivity.

Equations 9-12 reflect intergenerational capital transmissions as we estimate them in the Philippine data, much as equation 3 did in the simplified example above. Equations 13-15 reflect the impact of these capital transmissions on eventual child income, just like equations 4, 6 and 7 did in the simplified example.

$$\mathrm{E}_{ij} = \kappa^E y_j + \theta_E^E E_j + \theta_H^E H_j + \theta_L^E L_j + \zeta^E X_{ij} + e_{ij}^E \quad (9)$$
$$\mathrm{H}_{ij} = \kappa^H y_j + \theta_E^H E_j + \theta_H^H H_j + \theta_L^H L_j + \zeta^H X_{ij} + e_{ij}^H \quad (10)$$
$$\mathrm{L}_{ij} = \kappa^L y_j + \theta_E^L E_j + \theta_H^L H_j + \theta_L^L L_j + \zeta^L X_{ij} + e_{ij}^L \quad (11)$$

$$S_{ij} = \kappa^S y_j + \theta_E^S E_j + \theta_H^S H_j + \theta_L^S L_j + \zeta^S X_{ij} + e_{ij}^S \quad (12)$$
$$y_{ij} = \pi y_j + \lambda_i^{E1} E_{ij} + \lambda_i^{H1} H_{ij} + \lambda_i^{L1} L_{ij} + \zeta^{y1} X_{ij} + e_{ij}^y \quad (13)$$
$$y_{ij} = \mu y_j + \lambda^{E1} E_j + \lambda^{H1} H_j + \lambda^{L1} L_j + \zeta^{y2} X_{ij} + e_{ij}^y \quad (14)$$
$$y_{ij} = \omega y_j + \lambda^{E2} E_j + \lambda^{H2} H_j + \lambda^{L2} L_j + \lambda_i^{E2} E_{ij} + \lambda_i^{H2} H_{ij} + \lambda_i^{L2} L_{ij} + \zeta^{y3} X_{ij} + e_{ij}^y \quad (15)$$

The variables y_j, E_j, H_j, and L_j give parent income, education, health, and land value respectively for household *j*, with E_j and H_j as vectors that contain education and health levels for both parents. The variables E_{ij}, H_{ij}, L_{ij}, S_{ij} and y_{ij} give child *i*'s adult educational attainment, adult health status, adult landholdings, spouse educational attainment, and adult income, respectively. The vector X_{ij} contains household size (since this constrains parent transmissions through the budget constraint) and variables that control for social norms (ethnic group, childhood district, birth order dummies).

The coefficient κ^C estimates the effect of parental income on child accumulation of capital of type *c*, reflecting liquidity effects on child capital accumulation beyond intergenerational capital transmission *per se*. The coefficient θ_p^C estimates the direct transmission to child capital *c* from parent capital *p*. Note that we allow explicitly for cross-capital influences, such as the effect of parental health or landholdings on children's education.

In equation 13, the more general version of equation 4 above, the parameter π reflects the impact of parental income independent of its effect on child capital accumulation, i.e. the effect of productivity transmission. Estimating this equation allows us to test the hypothesis that $\pi = 0$, implying the absence of productivity transmission. The parameter vector λ_i^{c1} represents the returns to child *i*'s stock of capital *c* in the restriction specification.

By contrast, in equation 14 (the generalization of equation 6 in the simple example above), the parental income coefficient μ estimates the combined influence of parent income on ultimate child adult income – that is, the cumulative effect of parental income on child productive capital accumulation through relaxed liquidity constraints, independent of direct intergenerational capital transmission, plus intergenerational correlation in productivity. The coefficient λ^{p1} estimates the combined influence of all direct transmissions from parent capital *p* on ultimate child income. Estimating equation 14 as well as equation 13 allows us to test the hypothesis that $\pi = \mu$, implying that liquidity constraints do not affect child capital accumulation.

Equation 15 is the most general form, which allows us to test the exclusionary restriction that the vector $\lambda^{p2} = 0$, signaling that parental capital has no direct effect on child income, but only operates through child capital accumulation and productivity transmission. This most general specification also lets us test the complementary hypotheses that $\omega = \pi$ and that $\lambda_i^{c1} = \lambda_i^{c2}$, implying that intergenerational productivity transmission and the returns to different forms of child capital are all invariant to parental capital endowments.

The relative magnitudes of these coefficients have direct policy implications. If the κ^C income transmission coefficients are significant and large then child capital levels are normal goods, and infrastructure such as better public schools, free health clinics in rural areas or more aggressive tax policies can mitigate intergenerational capital accumulation. If μ is also large, such policies might also mitigate eventual intergenerational income transmission. Of course, income transmission coefficients could be large but μ small, reflecting low returns to human capital. Or income transmission coefficients could be small but μ large, signaling high rates of intergenerational correlation in productivity. If income transmission coefficients and μ are both small, however, and instead the direct capital transmission coefficients are large, then change in parent capital levels may be necessary to improve social mobility, implying a need for programs that reach out specifically to low-capital parents and their children. That is why it becomes important to test the exclusionary restriction that parent capital exerts no influence on child adult income independent of parental income (the intergenerational productivity transmission parameter) and child capital accumulation (the returns to capital parameters).

4. Data

The data were gathered over the course of two decades in Northern Mindanao District in the Philippines. The first round of data was gathered over four waves in 1984/85, in a rural, landlocked province called Bukidnon. This survey, under the Philippines Cash Cropping Project, was focused on household effects of agricultural commercialization. It sampled 510 families from rural Bukidnon, almost all of whom relied heavily on agricultural income.

The second round of data was gathered by the International Food Policy Research Institute (IFPRI) and the Research Institute for Mindanao Culture (RIMCU) in 2003/04, using a questionnaire highly similar to the one from 1984/85. This survey, called the Bukidnon Panel Survey (BPS) in 2003/04, was administered to three types of families. First, it interviewed all original households still living in the original survey area, a total of 311 households (61 percent of original respondents). During this survey, original respondents listed all non-coresident children, and also provided basic information about many of these children including location, educational attainment, and marital status. Also during this survey, coresident children were interviewed. However, we do not include data from coresident children in this paper, given that they are not usually "head of their households" or earning their own income.

Second, it sampled at random up to two non-coresident children near their original (parent) household, a total of 261 households. We refer to these children as "splits" for the rest of the paper. Third, it sampled non-coresident children living further away from their parent household. These children, who we refer to as "migrants," were living in the three urban areas in Mindanao, or in municipality seats, or in other rural areas of Bukidnon. About 75 percent of potential migrants were interviewed, for a total of 257 migrant households. For a more detailed description of these data, see Quisumbing & McNiven (2009).

Original families who were found and re-interviewed in 2003 are notably different in 1984 than families which were not found in 2003. The former are significantly larger, with more children, and headed by individuals who are older and migrated to their 1984 location earlier. They own more land, depend more heavily on home-produced food, income from cash cropping and corn, and depend less heavily on non-agricultural sources of income and agricultural wage labor. They also have higher income and expenditure levels. Most of these differences are significant at the one percent level, and all at the five percent level. Given such attrition effects, the intergenerational transmission trends discussed in this paper should be considered specific to the sample of families who remained in Bukidnon through 2003. While it seems likely that family-level migration would change subsequent intergenerational transmission trends, such analysis is unfortunately impossible with these data.

In this paper, parent variables (such as parent income, parent height, and parent educational attainment) are usually taken from the 1984 survey, but occasionally taken from the 2003 survey when it seems more appropriate. These instances are explained in section 5. We use child attributes (such as child income, child height, and child educational attainment) from the 2003/04 surveys of split and migrant children.

Table 1 displays summary statistics for male children, female children, splits (i.e., non-migrants) and migrants. A series of t-tests shows that there is no significant difference between migrants and splits during childhood, except that male migrants tend to be of a slightly lower birth order, averaging around third-born while the male splits average around 2.5-born. By adulthood, however, there are discernible differences between migrants and splits. Both male and female migrants are significantly more educated, have significantly greater incomes, and are significantly less likely to be married than splits. There is no difference in height across adult migrants and splits.

Since t-tests suggest that migrants and splits are similar as young children, it seems unlikely that parents invest in their children's capital levels according to future migrant status. We thus analyze intergenerational capital transmissions separately for males and females, but not separately across splits and migrants. Migration has occurred, however, by 2003 when children are married, living in their new houses, and earning income. By this time there are discernible differences between splits and migrants, and it seems plausible that migrants might experience different intergenerational income mobility trends than non-migrants. For this reason, we analyze and decompose IGE separately for males, females, migrants and splits. In these final regressions we control for gender when grouping children by migrant status (since gender certainly effects income), but we do not control for migrant status when grouping children by gender (since we consider migrant status potentially endogenous to child capital levels).

It is important to note that there is very little selection bias in the choice of siblings who were tracked in 2003/2004. An examination of their sex, age, health, education levels, and height and weight z-scores shows that the children tracked by the BPS survey were not significantly different in 1984 than their siblings except by sex, age and birth order. (See Appendix 1.) Tracked children were significantly less likely to be male, and were of

significantly greater age and higher birth order. Since older children were more likely to have moved out of their parents' house by 2003/2004, the difference in age and birth order is expected and does not imply any difference in other characteristics; it likely just reflects life cycle effects for which we control anyway. Tracked children are more often female children largely because females migrated more often than male children, and so a higher proportion of the migrant children tracked in 2004 were female. Even of the "split" children closer to home, however, slightly more female children were tracked than male children, a difference that is statistically significant at the ten percent level. Since we present all results across sex, this selection issue does not affect any of our results except inasmuch as it decreases sample size for male children.

Throughout this paper, the variables education and spouses' education are measured in years of schooling completed,[3] land is measured in hectares owned, and height is measured in centimeters. Income and expenditure measures are expressed in log terms. We use height as the indicator for parent and child health for two reasons. First, height is a good measure of health stock, in that it captures the final outcome of many years of varying health investments and health shocks (Thomas 1994). Second, full height is attained roughly simultaneously with the completion of education, both under the auspices of parental guidance and investment. Thus, it represents childhood health formation, heavily weighting the earliest years of life rather than later health conditions attained once a child is living separately from his or her parents.

5. Estimation Strategy

Throughout the paper we adjust for measurement error in and transitory shocks to parent income by instrumenting for parent income with parent expenditure, which better reflects permanent income.[4] We instrument this way, rather than averaging multiple periods' income observations, because the BPS contains only two rounds of parent income data. Under classical measurement error, but especially under the time-persistent measurement error that is likely to exist around structural income (Mazumder 2005, Naschold & Barrett

[3] Ideally, one would include measures of child cognitive ability or performance as yet another form of intergenerational capital transmission. Unfortunately, no such variables exist in these data. Thus, the transmission of cognitive ability is captured only within the productivity transmission measured in equations 13 and 15.

[4] Note that we instrument not to address an endogeneity issue, which would require a plausible exclusionary restriction, but rather to obviate an error-in-variables problem that would otherwise lead to attenuation bias in the IGE estimates. This does imply, however, that if parent expenditures were to (positively) affect future child income in any way except through correlation with a parent's permanent/structural income, the coefficient estimate on parent income might be biased (upwards) in all capital and income transmission regressions. We therefore tested the exclusionary restriction by regressing child income on both parent income and parent expenditure. In 15 of 18 cases, we could not reject the null hypothesis that parent expenditure had no independent correlation with child income in favor of the alternate hypothesis of a positive correlation. Details of these tests are available by request. In the few cases where the exclusionary restriction does not hold (noted in the text), the non-adjusted and adjusted estimates of the parent income coefficient may be viewed as lower and upper bounds, respectively, around the true IGE coefficient. The qualitative story is nonetheless consistent whichever of those estimates one prefers.

2011), two rounds of data will not significantly mitigate attenuation bias on income transmission or IGE estimates.

This instrumental variables strategy eliminates measurement error bias in estimated income coefficients if measurement error around structural income is orthogonal to measurement error around expenditure. For any random component of measurement error, for instance misreporting or misrecording error, such orthogonality seems likely. Orthogonality may seem less likely to hold for error due to transitory income shocks. But a test finds strong evidence of consumption smoothing that makes this assumption plausible. (See Appendix 2).

Consistent with prior results in the literature, instrumenting for single year income with expenditure, as a proxy for permanent income, results in a significantly higher IGE estimate than does averaging across just two periods. Table A4 in Appendix 2 compares these estimates for the entire sample of children and for sub-samples selected by gender and migrant status.

We use 1984 parent income/expenditure measures rather than 2003 parent income/expenditure measures, for three reasons. First, the 1984 measures better predict child income and asset levels. Second, we wish to capture the causal pathways between parent and child income, and the capital transmissions that we hypothesize serve as these pathways occur primarily during childhood and young adulthood. The structural income of parents in 1984 ought to hold more information about these pathways than the structural income of parents in 2003. Third, 2003 parent expenditures may, to some extent, reflect remittances from migrant and split children, and we are interested in isolating the mechanisms behind IGE that flow from parent to child rather than the other way around.

The estimation of equations 9-15 represents the primary contribution of this paper. Because capital transmissions are likely to share an error structure for any given child, we estimate equations 9-12 simultaneously, correcting for likely measurement error in parent income using Three Stage Least Squares (3SLS).[5] Those results appear in Tables 2 and 3. We estimate Equations 13-15 using ordinary least squares, instrumenting parent income with parent expenditure.

Because land inheritance and spouse capital levels are determined in the same period as migrant status (which indicates whether a child moves outside of their parents' *barrio*, or geographic area), we do not control for migrant status in equations 11 and 12. We treat migrant status as an intermediary outcome, itself a consequence of parent capital levels. Rather than being a form of human capital in and of itself, migration changes the return to human capital, such as education, by affording one access to different labor markets (Mude

[5] One might also hypothesize that a separate error structures exists for childhood transmissions (that of education and height) and young adult transmissions (that of land and spouse capital). This assumption would suggest two separate estimations of the (sub)systems of equations, which leads to almost identical results as displayed in Tables 2 and 3. We go with the less restrictive assumption. The other results are available upon request.

et al 2007). However, the estimation results are robust to both including migrant status as a control variable in equations 11 and 12 and also estimating a fifth "transmission" equation along with equations 9-12, which gives migrant status as a function of parent capital levels (results available on request).

As mentioned earlier, decomposing IGE into parent-to-child capital transmissions does not necessarily illuminate the mechanisms behind these pathways. Knowing that mother's education is associated with an increase or decrease in child health, for instance, does not illuminate the behaviors or circumstances which create such an association. In order to begin exploration of such mechanism, we add controls to the decompositions given by Equations 9-12, after estimating those equations on their own. These controls allow some informed speculation as to the causal mechanisms behind important IGE pathways. These details are discussed in the subsections that follow.

6. Results

Tables 2 and 3 displays estimates of intergenerational human and physical capital transmission for daughters and for sons, respectively. The regressions shown in each table were estimated simultaneously via 3SLS, instrumenting for parent income with parent expenditure. In each table, columns 1 and 2 reflect education and height transmission, respectively, and columns 3 and 4 estimate landholding and spouse education transmission, respectively. We will discuss each of these capital transmissions in turn, and then examine and decompose intergenerational income transmission.

The parent capital variables in Tables 2 and 3 are correlated but not multicollinear. The tolerance of each parent capital variable, with respect to all other parent capital variables, ranges from 0.54 to 0.99, with a mean variance inflation factor of 1.42. Furthermore, capital transmission regressions that control for one parent capital level at a time, as a check on the robustness of the relative associations between parent and child capital levels in Tables 2 and 3, generate very similar results (details available by request). While several point estimates increase when parent capital levels are controlled for individually – almost certainly due to omitted variable bias – the relative magnitudes of coefficients both within and across transmission equations remains largely unchanged.

Education Transmission

Parental income exerts a statistically significant positive effect only on sons' education, with an effect that is statistically significantly greater than that for daughters.[6] Note that free public primary school had been long established by 1984, when round 1 of the BPS was conducted, and free secondary school was established in 1988. These results suggest that despite free government education, child education is a normal good, but with the education-income association having both a larger magnitude and greater variation for sons than for daughters.

[6] Moreover, the coefficient estimate on parental income may be biased upward in the daughters' education equation because we reject the exclusionary restriction on parent expenditure, which we use to instrument for parent permanent/structural income. Parent expenditure has a positive correlation with daughters' education independent of parent income.

Direct intergenerational education transmission clearly occurs, especially from mothers to children. The magnitude of the estimated effect of the mother's education is two to three times that of the father's education and strongly statistically significantly different from zero. A father's education has no statistically significant effect on sons' education, but does have a significant effect on daughters' education. There is, however, no statistically significant difference between the effect of a father's education on daughters and on sons. Curiously, mother's height is negatively and statistically significantly related to daughter's education, which may reflect an increased need for daughters to provide domestic work given the higher labor market opportunity cost of taller mothers' time.

Height Transmission

As with a mother's education, mother's height positively and significantly impacts the height of both sons and daughters, while a father's height has only a significant impact on the height of sons. For daughters, the impact of mother's height is 4.5 times greater than and statistically significantly different from that of the father's height. The association between mother's height and son's height is only a third again the magnitude of that between father's height and son's height, though this difference is statistically significant.

The negative, statistically significant relationship between mother's education and daughter's height is striking, as was the negative relationship between mother's height and daughter's education. Again, this effect may relate to maternal labor supply. A variety of authors have showed that maternal labor supply and/or a mother's feeding practices, both of which might be associated with a mother's education or height, can influence child development (Leslie 1989). A more educated mother might be less likely to breastfeed her child, for example. Indeed, in our sample mother's education is positively correlated with bottle feeding. Blau et al (1996) find that both mother's labor supply and mother's wages are negatively associated with breast-feeding in rural Philippines. Their results show, however, that increased maternal labor supply actually improves childhood health in the long run, with perhaps questionable impacts in the very first months.

Poor data on child feeding practices prevents us from estimating the association between maternal labor supply or feeding practices and daughter's height in 2003. However, Table 4 illustrates the association between maternal labor supply, feeding practices and mother's birth-age on height-for-age z-scores (HAZ) for children under five years of age in 1984. Note that this regression includes those children in the 1984 survey who were not followed during the 2003/4 survey. Controlling for child feeding practices does change the sign on mother's education from negative to positive for daughters, although this is not true for sons. These results are suggestive only, but leave open the possibility that negative associations between a daughter's human capital and mother's height or education level may be a result of maternal labor supply.

Land Transmission

The principal determinant of child adult landholdings is parent landholdings, although the impact of parent landholdings on son's landholdings is about four times greater than and statistically significantly different from the impact of parent landholdings on daughter's

landholdings. This is not surprising since two-thirds of the land inherited in our sample went to sons, and only one-third to daughters. No other factors significantly affect the landholdings of daughters, but both parent income and father's height negatively predict son landholdings.

These results are unsurprising given the shift in occupational categories across generations. In 1984, the wealthiest, tallest, and often most educated parents were the landholding parents who grew sugar or corn, the most remunerative crops in the region. By 2003/2004, however, the wealthiest and most educated children (though not the tallest) held professional jobs such as government officials or teachers. These professional children are more likely than other children to come from tall, landholding families, and they hold land at slightly higher rates than other children. Yet land is unnecessary for their primary job by 2003, a major transition in just one generation. Expressed differently, in 1984 the bivariate correlation coefficient between parent landholdings and parent income was 0.719. In 2003/4 that correlation coefficient for parents had fallen to 0.639. More strikingly, the coefficient between child landholdings and child income was just 0.275 in 2003. While 56 percent of parents held at least some land in 2003/4, only 11 percent of children held land in 2003/4. While almost 100 percent of parents worked in the agricultural sector in 1984, only about a quarter of the children surveyed in 2003/4 list agricultural work as their primary occupation. Takahashi (2013) finds similar generational trends when it comes to occupation and agricultural income in the rural Philippines.

Spouse Education

Parent income is only weakly associated with the education level of a daughter's spouse, and is not significantly associated with the education level of a son's spouse. (See the last columns of Tables 2 and 3.) As with human capital transmission, mother's education is significantly and positively associated with spouse education for both sons and daughters, though the magnitude of this impact is statistically significantly higher for sons than for daughters. Father's education is positively and significantly related to the education of a daughter's spouse, and at roughly similar magnitude, but not to the education of a son's spouse.

Given the illustrated existence of parent-to-child education transmission, it seems possible that the impact of parent education on spouse education might work independently of or through child education. While we do not display the results here, controlling for child education directly in equation 12 (i.e., the fourth columns of Tables 2 and 3) suggests that the influence of Philippine parents on the education levels works mainly through their influence on child education levels. DeSilva and Bakhiar (2011) use similar regressions to test the validity of parent education as an instrument for child education. They support the theoretical validity of this instrument by noting that in the Philippines families play a relatively minor role in the choice of marriage partners. Indeed, only thirty percent of the women in their sample were introduced to partners by parents or other family members.

Taken together, the results displayed in Tables 2 and 3 suggest that the transmission of mother's human capital may be less gender-specific and generally stronger than the transmission of father's human capital. Quisumbing (1994) and Estudillo et al (2001b)

found similar patterns of gender-specific intergenerational capital transmissions in the Philippines. However, there is no clear pattern of which child is "favored" by higher paternal transmissions. While a father's education has a stronger impact on the education of daughters than on sons, a father's height has a stronger impact on the height of sons than daughters.

Income Transmission

The preceding estimates establish that intergenerational capital transmission is statistically significant and of considerable magnitude in many cases, especially with respect to human capital and landholdings. This motivates the decomposition of intergenerational income transmission (IGE) presented in Tables 5-8. These tables gradually decompose IGE according to equations 13-15 for daughters (Table 5), sons (Table 6), migrants (Table 7) and non-migrants (Table 8).

Given that migrants comprise a non-random selection of the broader child population, and since migrant status is likely determined by factors that also affect income, the coefficient estimates in Tables 7 and 8 may be biased. Heckman correction model estimates (available by request), however, find the coefficient estimate on the migrant selection covariate statistically insignificant in all cases, and find almost no change in other coefficient estimates.

The first column of each table (5-8) displays naïve IGE estimates, corresponding to equation 1. These regressions instrument parent income with parent expenditure, and control only for child age and parent age quadratically, in order to control for life cycle effects. The second columns of each table display the same regression, but controlling additionally for location, ethnicity, household size and gender-specific birth order. (These same controls were used in Tables 2 and 3.)

The IGE figures estimated in the first columns of Tables 5-8 are high, but consistent with the existing literature. Takahashi (2013) estimates IGE in the rural Philippines, uncorrected for measurement error, to be approximately 0.22. This is similar to our own findings when we use OLS regression to estimate IGE (see Table A4 in Appendix 2). Mazumder (2005) and Behrman and Taubman (1990) find IGE estimates of over 0.5 in the US when measurement error is properly controlled for, and Salon (2002) compiles a table of IGE estimates from outside the US which range from 0.11 to 0.57.

While IGE is highest for daughters and migrants, there is no statistically significant difference in IGE across ether gender or migrant status.[7] It is interesting to note, however, that the R^2 of column 1 in Table 5 is more than double that of column 1 in Table 6, indicating that parent income better explains daughter income than son income.

[7] The coefficient estimate on parental income in column 1 of the sons' income equation may be biased upward, however, because we reject the exclusionary restriction on parent expenditure, which has a positive correlation with sons' income independent of parent income. The same is true for column 2 of the daughters' income equation.

Controlling for ethnicity, location, household size and birth order in the second column of each table increases the R^2 for sons by a factor of 7, and for daughters by a factor of almost 3. From these two columns alone, it seems clear that family capital, income and/or productivity plays a larger part in deciding daughters' adult income than sons' adult income, which seems to better explained by structural factors such as ethnicity and location. While one might be tempted to assume that this difference is due to the higher proportion of daughters who migrate (50 percent of daughters as opposed to 37 percent of sons), the R^2 actually increases less from column 1 to column 2 for splits than it does for migrants.

The third columns of each table include parent capital levels as additional regressors, following equation 14, illustrating the influence of parent-to-child capital transmissions on IGE. Mother's education and parent income are the only statistically significant predictors of a daughter's adult income. The importance of mother's education is unsurprising given its importance to a daughter's education and to the education of a daughter's spouse through assortative marriage. What is striking and perhaps surprising, however, is that parental income exerts such strong influence over daughters' adult income, even controlling for parental capital stocks.

For sons, parent landholdings and mother's height are the only statistically significant predictors of income. The importance of land is unsurprising given the intergenerational land transmission to sons displayed in Table 3 and the fact that farming is a male-dominated occupation in this part of the Philippines. The negative impact of maternal height on son income is somewhat puzzling but may follow from the negative, although statistically insignificant, maternal height transmissions to son landholdings. Since maternal height has a significantly positive impact on son's height, it would appear that son's height is not a significant predictor of son's income. This is perhaps unsurprising given the demographic and occupational shifts discussed earlier.

When broken down by migrant status there is no significant contribution of parent capital to child income. This further suggests that parent capital transmissions are based on child gender rather than on migrant status. The coefficient estimate on parent income, however, is significant for migrants, splits, and daughters. In fact, this coefficient increases in magnitude from column 1 to column 3 for daughters and for migrants. It decreases and becomes statistically insignificant for sons, and decreases slightly (although it remains statistically significantly different from zero) for splits. Apparently, parent income is even more important to daughters' adult earnings and to migrant earnings than the naïve IGE estimate would suggest – signaling that intergenerational capital transmissions bias this estimate downwards – while the opposite is true for the adult earnings of sons. The IGE estimate appears to just about perfectly capture the combined impact of liquidity constraints and productivity transmission on adult earnings of non-migrants, however.

By controlling for child capital levels themselves in the fourth and fifth columns of Tables 5-8, following equations 13 and 15, we isolate the contribution of intergenerational productivity transmission (or perhaps intergenerational transmission of unobserved forms of productive capital), as the coefficient estimate on parent income. These coefficients are

significant and large for daughters, slightly smaller for splits, and insignificant for sons. These point estimates are only slightly smaller for migrants than for splits, but with much greater variability. This could reflect a smaller sample size for migrants, but might also reflect true variability in productivity transmission to migrants. Such variability would be logical if some migrants are "escaping" poverty and poor social networks at home while others are sent on a wave of parent connections and ability. The magnitude of the parent income coefficient estimate is almost but not quite the same across columns 4 and 5 of Table 5, as predicted in section 3. A Wald test rejects the null that these coefficients are identical for daughters (p=0.0413) and for splits (p=0.0076), suggesting that productivity transmission is not impervious to parent capital levels. The same test cannot reject the possibility these coefficients are equal for migrants, which is perhaps unsurprising given the variability around productivity transmission to migrants.

The fact that these point estimates on parent income for daughters (Table 5) fall in magnitude from column 3 to columns 4 and 5, albeit not significantly, suggests that parent income plays a role in shaping daughter income through investment in child capital accumulation. This underscores the normal good characteristic of daughters' education, although Table 5 suggests that the biggest impacts come through the marriage market. The large and statistically significant point estimates on parental income even controlling for child and parent capital, however, clearly indicate a role for productivity transmission in shaping daughters' adult income. Conversely, the coefficients on parent income in columns 3-5 of Table 6 suggest that parent income and productivity transmission play little role in shaping sons' adult income. The gender difference is striking and novel in this literature.

Furthermore, the point estimates on parent income for migrants (Table 7) fall sharply in magnitude and becomes statistically insignificant from column 3 to columns 4 and 5. The same estimate remains statistically indistinguishable across columns 3, 4, and 5 for non-migrants (Table 8). Because we suppose from the start that parents to do not invest in child capital differently across migrant status, it seems unreasonable to suppose that parents consider migrant capital investments (and not split capital investments) as normal goods. Possibly the difference stems from the fact that females make up a higher proportion of migrants than splits, and thus by virtue of the greater preponderance of females among migrants, parent liquidity is more important to the capital accumulation of migrants than splits purely by virtue of the gender differentiation already noted.

The last two columns of Tables 5 and 6 illustrate that child landholdings are important predictors of child adult income, in spite of the marked transition toward non-farm occupations. Oddly, given the gendered nature of land inheritance and farming in this region of the Philippines, the association between landholdings and income is significantly stronger for daughters than for sons. This cannot be explained by the overlap between daughters and migrants, since migrants quite logically experience no significant income returns to land, as opposed to splits who experience the highest income returns to land.

Spouse education is also an important predictor of child adult income, though the magnitude of this coefficient is four times greater for sons than for daughters, and statistically significantly different. There is no significant difference between the influence

of spouse education for migrants and non-migrants. While own education appears to be a significant predictor of education for all groups but daughters in column 4, the magnitude of this coefficient decreases so as to be insignificant for all groups in column 5.

A Wald test rejects the exclusionary restriction implied by equations 13-15 for sons (p=0.0023) but not for daughters (p=0.1208). In particular, both mother's height and father's height remain negatively associated with son income in column 5 of Table 6. And while parent capital levels as a whole are jointly insignificant in Table 5, mother's height and mother's education remain individually significantly positively associated with daughter income in column 5 of Table 5. A second Wald test does reject the exclusionary restriction with respect to mother's education and height only. A Wald test rejects the exclusionary restriction implied by equations 13-15 for both migrants and splits.

It seems probable that, like the coefficient estimate on parent income, the coefficient estimates on parent human capital levels capture the impact of some sort of productivity inheritance or correlated intergenerational transmission of an omitted capital stock. For example, perhaps mother's education and height aid a daughter's success in the marriage market irrespective of the husband's education level. Or perhaps by increasing a son's agricultural productivity and thus increasing his chance of working in the agricultural sector, parent height actually decreases a son's economic productivity by diverting him from the more remunerative non-farm sector. The negative impacts of both father's education and parent land on migrant income are curious and bear further investigation.

7. Conclusions

This paper documents high intergenerational income elasticity (IGE) in the rural Philippines and then illustrates that decomposing IGE estimates into its constituent capital and productivity transmission pathways is both possible and useful. Examining intergenerational capital transmission and intergenerational income elasticity jointly enhances our understanding of the mechanisms underpinning IGE and allows us to compare the importance of parent income and parent capital to child capital formation.

Perhaps the most important conclusion that can be drawn from our results is of sharp gender differences in the pathways of intergenerational income transmission in the rural Philippines. Although the naïve IGE estimates are statistically indistinguishable for sons and daughters, the pathways that generate these results differ strikingly. Parent income *per se* actually plays no direct role in the transmission of parent income to sons. Rather, productive capital is transmitted across generations, especially in the forms of education, health and landholdings. Financial liquidity constraints are less important to sons' productive capital accumulation and adult income than are parental capital endowments, which may transmit directly (as in the case of height, due to genetics and behaviors) or via parental expectations and preferences. Sons' education and sons-in-law's education are the only two child capital stocks that are strongly and positively affected by parent income, indicating that "son education" (whether biological or married in) is a normal good.

By contrast, while intergenerational capital transmission completely explains the IGE for sons, parental income exerts a very strong independent effect on daughters' adult income and that effect increases rather than falls as one adds controls for parent and/or child capital stocks. Daughters' income appears heavily influenced by success in the marriage market, which is in part driven by her own education (shaped in large part by maternal education), and in part driven by the effects of parent income. Daughters' adult income also exhibits considerable intergenerational productivity transmission, possibly related to social networks and again working through the marriage market. In contrast, parent income seems to play very little role in obtaining a "valuable" wife for sons through the marriage market; parent endowments transmit more directly to son's endowments.

While it is sometimes difficult to distinguish patterns differentiated by gender from those according to migrant status, it is clear that the pathways behind IGE also differ for migrants and non-migrants. Parental investment in migrant capital seems constrained by parent liquidity, like that of daughters and perhaps because such a high proportion of migrants are daughters. Investment in non-migrants does not appear to be constrained in the same way. The productivity transmission to non-migrants is much higher than that to migrants, which seems logical given that children who live close to their parents continue to share with them social networks and other factors that affect productivity. The variability around productivity transmission for migrants is notably high, much higher than for any other group. This may imply a large variation in the benefits of social networks and other family assets available to migrants, which would be logical if both "pull" and "push" factors influence a child's decision to migrate.

Additionally, it seems generally true that while mothers transmit human capital relatively equally and statistically significantly to both sons and daughters, fathers' human capital is less important to children in general and often affects the capital level of only daughters or only sons. Mothers' education is particularly important to eventual child income because it is strongly and positively associated with both own and spouse education, each of which is, in turn, strongly associated with child adult income.

These findings carry significant policy implications. Policies focused on obviating the effects of parent income inequality appear likely to have a pronounced effect on females' intergenerational economic mobility but negligible effects on the intergenerational economic mobility of sons in BPS communities. Rather, for sons, the intergenerational transmission of capital levels must be mitigated in order to enhance equality of opportunity across generations.

This decomposition approach to understanding the intergenerational elasticity of income sheds greater light on the multiple, parallel processes underpinning economic mobility than do simple statistical associations such as naïve IGE estimates or a simple regression of child education on parent education. While this analysis necessarily falls short of identifying the causal pathways that might most effectively permit policymakers to enhance equality of opportunity, decomposing the direct and income transmission avenues allows us to narrow the range of mechanisms worth exploring through more meticulous structural or experimental empirical work.

8. References

Asadullah, M. Niaz. 2012. "Intergenerational wealth mobility in rural Bangladesh," *Journal of Development Studies,* 48(9):1193-1208.

Becker, Gary S. 1974. "A Theory of Social Interactions." *Journal of Political Economy*, 82(6): 1063-1093.

Becker, Gary S. and Nigel Tomes. 1979. "An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility," *Journal of Political Economy*, 87 (6): 1153-1189.

Beegle, Kathleen, Joachim De Weerdt, Stefan Dercon. 2011. "Migration and economic mobility in Tanzania: evidence from a tracking survey," Review of Economics and Statistics, 93(3): 1010-1033.

Behrman, Jere R. 1997. "Women's Schooling and Child Education: A Survey." Mimeo, University of Pennsylvania.

Behrman, Jere, Alejandro Gaviria, Miguel Szekely, Nancy Birdsall, Sebastian Galiani. 2001. "Intergenerational mobility in Latin America," *Economia*, 2(1):1-44.

Behrman, Jere, Mark Rosenzweig. 2002. "Does increasing women's schooling raise the schooling of the next generation?" *American Economic Review,* 92(1):323-334.

Behrman, Jere, Paul Taubman. 1990. "The intergenerational correlation between children's adult earning and their parent's income: results from the Michigan panel survey of income dynamics," *Review of Income and Wealth,* 36(2):115-127.

Bhalotra, Sonia, Samantha Rawlings. Forthcoming. "Gradients of the intergenerational transmission of health in developing countries," *Review of Economics and Statistics.*

Bhalotra, Sonia, Samantha Rawlings. 2011. "Intergenerational persistence in health in developing countries: the penalty of gender inequality," *Journal of Public Economics,* 95(3-4):286-299.

Black, Sandra, Paul Devereux. 2011. "Recent developments in intergenerational mobility," chapter 16 in David Card and Orley Ashenfelter, editors, *Handbook of Labor Economics, volume 4B:* 1487-1541 (Amsterdam: Elsevier).

Blau, David, David Guilkey, Barry Popkin. 1996. "Infant health and the labor supply of mothers," *Journal of Human Resources* 31(1):90-139.

Chadwick , Laura, Gary Solon. 2002. "Intergenerational income mobility among daughters," *American Economic Review*, 92(1):335-344.

Corak, Miles and Andrew Heisz. 1999. "The intergenerational earnings and income mobility of Canadian Men: evidence from longitudinal tax data," *Journal of Human Resources,* 34(3):504–533.

Costa, Dora L. 1998. "Unequal at birth: a long-term comparison of income and birth weight," *Journal of Economic History*, 58(4): 987-1009.

Currie, Janet, Enrico Moretti. 2007. "Biology as destiny? Short- and long-run determinants of intergenerational transmission of birth weight," *Journal of Labor Economics*, 25(2):231–264.

Dasgupta, Partha. 1997. "Nutritional status, the capacity for work, and poverty traps," *Journal of Econometrics* 77:5-37.

DeSilva, Sanjaya, Mohammed Mehrab Bin Bakhtiar. 2011. "Women, schooling and marriage in rural Philippines," Levy Economics Institute of Bard College, Working Paper No. 701.

Eriksson, Tor, Bernt Bratsberg, Oddbjørn Raaum. 2005. "Earnings persistence across generations: transmission through health?" Memorandum 35/2005, Oslo University, Department of Economics.

Ermisch, John, Marco Francesconi and Thomas Siedler. 2006. "Intergenerational mobility and marital sorting," *Economic Journal,* 116(513): 659-679.

Estudillo, Jonna, Agnes Quisumbing, Keijiro Otsuka. 2001a. "Gender differences in land inheritance, schooling and lifetime income: evidence from the rural Philippines," *Journal of Development Studies,* 37(4):28-48.

Estudillo, Jonna, Agnes Quisumbing, Keijiro Otsuka. 2001b. "Gender differences in land inheritance and schooling investments in the rural Philippines," *Land Economics* 77(1):130-143.

Fogel, Robert. 2004. "Health, nutrition, and economic growth," *Economic Development and Cultural Change,* 52(3):643-658.

Harris, John, Michael Todaro. 1970. "Migration, unemployment and development: a two-sector analysis," *American Economic Review* 60(1): 126-142.

Hertz, Tom, Tamara Jayasundera, Patrizio Piraino, Sibel Selcuk, Nicole Smith, Alina Verashchagina. 2007. "The inheritance of educational inequality: international comparisons and fifty-year trends," *B.E. Journal of Economic Analysis and Policy,* 7(2): article 10.

Jäntti, Markus, Bernt Bratsberg, Knut Røed, Oddbjørn Raaum, Robin Naylor, Eva Österbacka, Anders Björklund, Tor Eriksson. 2005. "American exceptionalism in a new

Light: A comparison of intergenerational earnings mobility in the Nordic countries, the United Kingdom and the United States," Warwick Economic Research Papers, No. 781, Department of Economics, University of Warwick.

La Ferrara, Eliana. 2007. "Descent rule and strategic transfers. Evidence from matrilineal groups in Ghana," *Journal of Development Economics,* 83(2):280-301.

Leslie, Joanne. 1989. "Women's work and child nutrition in the third world." In *Women, Work, and Child Welfare in the Third World*, eds. Joanne Leslie and Michael Paolisso, 19-58. Boulder: Westview Press.

Lewis, W. Arthur. 1954. "Economic development with unlimited supplies of labor," *Manchester School* 22(2):139-91.

Loury, Glenn C., 1981. "Intergenerational transfers and the distribution of earnings," *Econometrica*, 49(4): 843-867.

Maluccio, John, John Hoddinott, Jere Behrman, Reynaldo Martorell, Agnes Quisumbing, Aryeh Stein. 2009. "The impact of improving nutrition during early childhood on education among Guatemalan adults," *Economic Journal*, 119(537):734-763.

Mazumder, Bhashkar. 2005. "Fortunate sons: New estimates of intergenerational mobility in the U.S. using social security earnings data," *Review of Economics and Statistics,* 87(2):235-255.

Mude, Andrew, Christopher B. Barrett, John McPeak, Cheryl Doss. 2007. "Educational investments in a dual economy," *Economica* 74:351-369.

Naschold, Felix, Christopher B. Barrett. 2011. "Do short-term observed income changes overstate structural economic mobility?" *Oxford Bulletin of Economics and Statistics,* 73(5):0305-9049.

Núñez, Javier, Leslie Miranda. 2011. "Intergenerational income and educational mobility in urban Chile," *Estudios de Economia*, 38(1):195-222.

Österbacka, Eva. 2001. "Family background and economic status in Finland," *Scandinavian Journal of Economics*, 103(3): 467-484.

Pekkarinen, Tuomas, Roope Uusitalo, Sari Kerr. 2009. "School tracking and intergenerational income mobility: evidence from the Finnish comprehensive school reform," *Journal of Public Economics,* 93(7-8):965-973.

Piraino, Patrizio. 2007. "Comparable estimates of intergenerational income mobility in Italy," *B.E. Journal of Economic Analysis and Policy,* 7(2):1-15.

Quisumbing, Agnes. 1994. "Intergenerational transmissions in Philippine rice villages:

Gender differences in traditional inheritance customs," *Journal of Development Economics,* 43(2):167-197.

Quisumbing, Agnes R., Jonna P. Estudillo, and Keijiro Otsuka. 2004. *Land and Schooling: Transferring Wealth Across Generations*. Baltimore and London: Johns Hopkins University Press.

Quisumbing, Agnes, Scott McNiven. 2010. "Moving forward, looking back: the impact of migration and remittances on assets, consumption, and credit constraints in the rural Philippines," *Journal of Development Studies*, 46(1): 91–113.

Raaum, Oddbjørn, Bernt Bratsberg, Knut Røed, Eva Österbacka, Tor Eriksson, Markus Jäntti Robin Naylor. 2008. "Marital sorting, household labor supply and intergenerational earnings mobility across countries," *B.E. Journal of Economic Analysis & Policy*, 7(2).

Sakellariou, Chris. 2004. "The use of quantile regressions in estimating gender wage differentials: a case study of the Philippines," *Applied Economics* 36:1001-1007.

Solon, Gary. 2002. "Cross-Country Differences in Intergenerational Earnings Mobility," *Journal of Economic Perspectives,* 16(3):59-66.

Strauss, John, Duncan Thomas. 1998. "Health, nutrition, and economic development, *Journal of Economic Literature,* 36(2):766-817.

Takahashi, Kazushi. 2013. "Pro-poor growth or poverty trap?: estimating the intergenerational income mobility in rural Philippines," IDE Discussion Paper 382, IDE-JETRO.

Thomas, Duncan. 1994. "Like father, like son; like mother, like daughter: parental resources and child height," *Journal of Human Resources,* 29(4):950-988.

Thomas, Duncan. 1996. "Education across generations in South Africa," *American Economic Review,* 86(2):330-334.

Thomas, Duncan, John Strauss, Maria-Helena Henriques. 1991. "How does mother's education affect child height?" *Journal of Human Resources,* Vol. 26(2):183-211.

Table 1: Descriptive Statistics

	Mean Values Daughters	Mean Values Sons	Mean Values Migrants	Mean Values Non-Migrants
Child Age (years) '84	9.6	10.4	9.5	10.3
Father Age (years) '84	40	40	40	40
Mother Age (years) '84	36	36	36	36
Household Size (persons) '84	7.0	7.2	7.0	7.1
Father's Education (years) '84	5.0	5.2	5.0	5.2
Mother's Education (years) '84	5.9	5.6	5.9	5.6
Father's Height (cm) '84	161	161	161	160
Mother's Height (cm) '84	150	150	150	151
Parent Landholdings (hectares) '84	2.3	2.6	2.6	2.3
Parent Weekly Income (Philippine Peso)'84	270	301	288	279
Mother's Birth Age (years) '84	26	25	26	25
Child Birth Order (number, 1=eldest) '84	3.0	2.7	3.2	2.6
Child Height (cm)'84	122	128	122	127
Child Height-for-Age Z-score '84	-2.3	-2.3	-2.3	-2.3
Child Education (years) '84	3.2	3.3	3.2	3.3
Child Age (years) '03	29	30	29	29
Spouse Age (years) '03	29	32	32	28
Child Household Size (persons) '03	7.0	7.2	4.6	5.3
Child Education (years) '03	9.7	8.6	9.8	8.8
Spouse Education (years) '03	9.3	10.1	10.2	9.1
Child Height (cm) '03	150	163	155	156
Spouse Height (cm) '03	149	149	158	143
Child Landholdings (hectares) '03	0.1	0.3	0.2	0.2
Child Weekly Income (Philippine Peso) '03	1830	1805	2439	1326

Table 2: Intergenerational Capital Transmissions for Daughters (3SLS)

	(1) Daughter Education	(2) Daughter Height	(3) Daughter Landholdings	(4) Daughter Spouse Education
Log Parent Income ‘84	0.950	1.925	-0.0184	1.554*
	(0.766)	(3.084)	(0.128)	(0.872)
Parent Land ‘84/’03^	0.140*	-0.209	0.0434***	0.000371
	(0.0814)	(0.331)	(0.0125)	(0.0842)
Mother’s Education	0.343***	-0.762**	-0.0137	0.189*
	(0.0798)	(0.317)	(0.0166)	(0.114)
Father’s Education	0.170**	0.397	0.0157	0.252**
	(0.0830)	(0.330)	(0.0171)	(0.118)
Mother’s Height	-0.0874***	0.422***	-0.00874	-0.00359
	(0.0333)	(0.132)	(0.00682)	(0.0470)
Father’s Height	0.0217	-0.0181	-0.00896	0.00689
	(0.0305)	(0.121)	(0.00629)	(0.0434)
Observations	219	219	219	219
R-squared	0.581	0.243	0.331	0.410

Standard errors in parentheses
Controls include household size, gender-specific birth order dummies,
location (barrio) & ethnic groups dummies
^ Parent land is given by ’84 holdings in columns 1 and 2, and ’03 holdings in columns 3 and 4.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Intergenerational Capital Transmissions for Sons (3SLS)

	(1) Son Education	(2) Son Height	(3) Son Landholdings	(4) Son Spouse Education
Parent Income ‘84	3.185***	-1.013	-0.763**	0.653
	(1.145)	(2.042)	(0.362)	(0.917)
Parent Land ‘84/‘03^	-0.0447	0.279	0.163***	-0.0283
	(0.152)	(0.283)	(0.0281)	(0.0671)
Mother’s Education	0.312**	-0.0500	0.0224	0.365***
	(0.145)	(0.240)	(0.0507)	(0.135)
Father’s Education	0.137	0.272	0.00142	0.0266
	(0.124)	(0.208)	(0.0432)	(0.114)
Mother’s Height	0.0176	0.403***	-0.0178	0.0266
	(0.0584)	(0.0971)	(0.0206)	(0.0548)
Father’s Height	-0.00423	0.293***	-0.0378**	0.00505
	(0.0444)	(0.0735)	(0.0157)	(0.0419)
Observations	156	156	156	156
R-squared	0.393	0.459	0.351	0.346

Standard errors in parentheses
^ Parent land is given by ’84 holdings in columns 1 and 2, and ’03 holdings in columns 3 and 4.
Controls include household size, gender-specific birth order dummies,
location (barrio) & ethnic groups dummies
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Determining Height-for-Age (HAZ) in Children Under Five (OLS-IV)

	(1) Daughter HAZ	(2) Daughter HAZ	(3) Daughter HAZ	(4) Son HAZ	(5) Son HAZ	(6) Son HAZ
Parent Income '84	0.0371	-0.0145	0.00240	0.118	0.513*	0.471
	(0.420)	(0.400)	(0.406)	(0.371)	(0.307)	(0.327)
Parent Land '84	0.00435	0.00448	-0.0182	-0.00431	-0.0241	-0.0327
	(0.0735)	(0.0672)	(0.0647)	(0.0413)	(0.0351)	(0.0351)
Mother's Education	-0.0301	0.0223	0.0175	-0.0187***	-0.00993**	-0.0201
	(0.0452)	(0.0329)	(0.0311)	(0.00569)	(0.00475)	(0.0250)
Father's Education	0.0703	0.0307	0.0183	0.0357	0.0358	0.0306
	(0.0676)	(0.0424)	(0.0387)	(0.0352)	(0.0343)	(0.0324)
Mother's Height	0.0518**	0.0523***	0.0624***	0.0325*	0.0312**	0.0320**
	(0.0219)	(0.0162)	(0.0161)	(0.0170)	(0.0141)	(0.0138)
Father's Height	0.0295	0.0349**	0.0349**	0.0640***	0.0640***	0.0634***
	(0.0182)	(0.0156)	(0.0157)	(0.0146)	(0.0117)	(0.0116)
Ever Bottle-Fed		-0.234	-0.283		-0.274	-0.250
		(0.185)	(0.179)		(0.182)	(0.183)
Mother Birth Age			0.149**			0.0221
			(0.0686)			(0.0402)
Mother Work Hours			-0.0699***			-0.0473**
			(0.0203)			(0.0193)
Observations	315	291	291	360	345	344
R-squared	0.208	0.237	0.279	0.238	0.245	0.260

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Controls include household size, mother and father age, gender-specific birth order dummies, location (barrio) & ethnic groups dummies

Table 5: Decomposing Intergenerational Income Elasticity for Daughters

	(1) Income	(2) Income	(3) Income	(4) Income	(5) Income
Parent Income '84	0.534***	1.042***	0.919***	0.757**	0.721**
	(0.162)	(0.280)	(0.290)	(0.302)	(0.320)
Parent Land '84			-0.00935		-0.0348
			(0.0195)		(0.0229)
Mother's Education			0.0507*		0.0670*
			(0.0307)		(0.0370)
Father's Education			-0.00712		-0.0349
			(0.0300)		(0.0298)
Mother's Height			0.0130		0.0312**
			(0.0117)		(0.0122)
Father's Height			-0.00604		-0.00462
			(0.0136)		(0.0121)
Own Education				0.0453	0.0483
				(0.0347)	(0.0367)
Spouse Education				0.0399**	0.0387*
				(0.0201)	(0.0199)
Own Height				-0.00405	-0.00524
				(0.00830)	(0.00799)
Landholdings				0.283**	0.355***
				(0.124)	(0.125)
Age Controls:	Yes	Yes	Yes	Yes	Yes
Additional Controls:	No	Yes	Yes	Yes	Yes
Observations	240	236	236	216	216
R-squared	0.115	0.329	0.360	0.397	0.428

Standard errors in parentheses
Age controls include quadratic terms for child and father age
Additional controls include parent household size, gender-specific birth order dummies, location (barrio) & ethnic groups dummies
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Decomposing Intergenerational Income Elasticity for Sons

	(1) Income	(2) Income	(3) Income	(4) Income	(5) Income
Parent Income '84	0.429***	0.184	-0.306	-0.0918	-0.272
	(0.147)	(0.257)	(0.389)	(0.266)	(0.364)
Parent Land '84			0.0637**		0.0323
			(0.0318)		(0.0251)
Mother's Education			0.0588		0.0401
			(0.0395)		(0.0383)
Father's Education			0.0676		0.0218
			(0.0431)		(0.0325)
Mother's Height			-0.0425**		-0.0662***
			(0.0168)		(0.0195)
Father's Height			-0.0217		-0.0289**
			(0.0160)		(0.0131)
Own Education				0.0415*	0.0276
				(0.0252)	(0.0221)
Spouse Education				0.134***	0.130***
				(0.0251)	(0.0235)
Own Height				-0.000325	0.0219
				(0.0124)	(0.0141)
Landholdings				0.189***	0.130**
				(0.0581)	(0.0550)
Age Controls:	Yes	Yes	Yes	Yes	Yes
Additional Controls:	No	Yes	Yes	Yes	Yes
Observations	182	179	179	154	154
R-squared	0.050	0.350	0.434	0.544	0.593

Standard errors in parentheses
Age controls include quadratic terms for child and father age
Additional controls include parent household size, gender-specific birth order dummies, location (barrio) & ethnic groups dummies
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Decomposing Intergenerational Income Elasticity for Migrants

	(1) Income	(2) Income	(3) Income	(4) Income	(5) Income
Parent Income '84	0.567***	0.831***	1.092**	0.227	0.456
	(0.195)	(0.322)	(0.533)	(0.372)	(0.546)
Parent Land '84			-0.0551		-0.0447*
			(0.0461)		(0.0269)
Mother's Education			0.0802		0.0723*
			(0.0571)		(0.0390)
Father's Education			-0.0866		-0.0845**
			(0.0608)		(0.0382)
Mother's Height			0.00110		0.00877
			(0.0196)		(0.0194)
Father's Height			-0.0184		-0.0276
			(0.0220)		(0.0200)
Own Education				0.0777*	0.0750
				(0.0407)	(0.0474)
Spouse Education				0.0659**	0.0614*
				(0.0316)	(0.0329)
Own Height				0.00209	0.00315
				(0.00563)	(0.00643)
Landholdings				0.105	0.108
				(0.0863)	(0.101)
Age Controls:	Yes	Yes	Yes	Yes	Yes
Additional Controls:	No	Yes	Yes	Yes	Yes
Observations	185	182	182	148	148
R-squared	0.048	0.285	0.238	0.518	0.515

Standard errors in parentheses
Age controls include quadratic terms for child and father age
Additional controls include parent household size, gender-specific birth order dummies, location (barrio) & ethnic groups dummies
*** p<0.01, ** p<0.05, * p<0.1

Table 8 Decomposing Intergenerational Income Elasticity for Splits (Non-Migrants)

	(1) Income	(2) Income	(3) Income	(4) Income	(5) Income
Parent Income '84	0.474***	0.651***	0.524**	0.465***	0.527**
	(0.103)	(0.160)	(0.212)	(0.161)	(0.207)
Parent Land '84			0.0138		-0.0162
			(0.0168)		(0.0199)
Mother's Education			0.0269		0.0178
			(0.0358)		(0.0354)
Father's Education			0.0156		0.00157
			(0.0288)		(0.0263)
Mother's Height			-0.00290		-0.00543
			(0.0115)		(0.0126)
Father's Height			-0.0160		-0.0137
			(0.0101)		(0.0108)
Own Education				0.0399*	0.0345
				(0.0215)	(0.0226)
Spouse Education				0.0733***	0.0718***
				(0.0176)	(0.0176)
Own Height				-0.0110	-0.00200
				(0.0118)	(0.0133)
Landholdings				0.159	0.222*
				(0.107)	(0.118)
Age Controls:	Yes	Yes	Yes	Yes	Yes
Additional Controls:	No	Yes	Yes	Yes	Yes
Observations	237	235	235	224	224
R-squared	0.122	0.320	0.358	0.436	0.434

Standard errors in parentheses
Age controls include quadratic terms for child and father age
Additional controls include parent household size, birth order dummies and a dummy for sex, location (barrio) & ethnic groups dummies
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1

A1: Sibling Attrition (Differences between Tracked & Non-Tracked Siblings)

Variable	Mean for Tracked Siblings	Mean for Non-Tracked Siblings	T-test across Means
Male (dummy)	0.43	0.54	3.87***
Birth order (1=first, etc.)	2.86	3.53	5.88***
Age (years)	9.93	7.14	-8.66***
Education (years)	3.23	1.78	-9.85***
Height (cm)	125	110	1.84***
Height-forage (z-score)	-2.27	-2.32	-0.69
Weight-for-height (z-score)	-0.29	-0.43	-1.25
Ever bottle-fed (dummy)	0.38	0.41	0.46
Months breastfed (months)	12.7	13.1	0.39
Days sick in last 2 weeks (days)	0.88	1.01	1.53*

*** p<0.01, ** p<0.05, * p<0.1

Appendix 2

The BPS data display evidence of expenditure smoothing. Table A1 displays an OLS regression of 1984 parent income on household human and physical capital, parent age and parent occupation. Predicted income from this regression may be considered structural income, since the prediction is based on intransient household characteristics. Transitory income is thus constructed by subtracting this predicted income from observed income, and savings are constructed by subtracting observed expenditure from observed income.

If savings increase with transitory income, then families in the BPS dataset practice expenditure smoothing. If no expenditure smoothing occurs in these data, we would expect there to be no positive association between savings and transitory income. However, a univariate OLS regression, displayed in Table A2, rejects the null hypothesis that no relationship exists between savings and transient income. Indeed, we cannot reject the null that savings change one-for-one with transitory income. These results remain true also when controlling for a quadratic term for transitory income. Sample households appear to smooth consumption, thereby reinforcing the value of our instrumentation approach to mitigating bias caused by measurement error and transitory income shocks.

Consumption smoothing implies that transitory shocks to income in BPS communities, otherwise considered measurement error to structural income, the variable of interest, are not fully transmitted as transitory shocks to expenditure. Because error structures around observed income and observed expenditure are at most correlated but not identical, instrumenting for income with expenditure will mitigate the downward bias on IGE associated with measurement error around structural income of parents. Table A3 illustrates that indeed IGE estimates increase when instrumentation is used (column 4). Averaging income across years (column 3), which usually mitigates bias effectively when panels include six or more rounds of data, results in a much lower estimate of IGE. In fact, the coefficient on average parent income appears to reflect the difference between the predictive power of ’84 parent and ’03 parent income, more than a mitigation of measurement error.

Table A2: OLS Regression of Parent Income in 1984

	Parent Income 1984
Household size	49.84**
	(18.85)
Land owned (hectares)	-19.18*
	(9.823)
Average net worth of household in '84	0.00318***
	(0.000432)
Mother years of schooling	21.07**
	(9.459)
Father years of schooling	-9.315
	(6.879)
Mother height	2.265
	(3.325)
Father height	-0.729
	(2.488)
Age of father	-38.83**
	(16.47)
Age of father squared	0.528**
	(0.199)
Year father migrated to current location	-0.947
	(2.602)
Constant	755.5
	(745.6)
Observations	214
R-squared	0.934

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Additional controls: dummies for location (barrio), father's ethnicity, mother's ethnicity, location of father's birth, and family occupation;
counts by gender of household members within 4 age brackets (0-5, 6-10, 11-17, 18 & above)

Table A3: OLS Regression of Savings on Transitory Income

	(1) Savings	(2) Savings
Transitory Income	0.869***	0.851***
	(0.161)	(0.157)
Transitory Income Squared		0.00370***
		(0.00108)
Constant	-47.06***	-65.51***
	(11.37)	(12.32)
Observations	214	214
R-squared	0.121	0.167

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: IGE across Various Estimation Approaches

	(1)	(2)	(3)	(4)
Estimator:	OLS	OLS	OLS	IV
Dependent Variable:	Log Child Inc	Log Child Inc	Log Child Inc	Log Child Inc
Independent Variable:	Parent Inc ‘84	Parent Inc ‘03	Avg Parent Inc	Parent Inc ‘84
Instrument:	NA	NA	NA	Parent Expen ‘84
IGE All Children:	0.289***	0.167***	0.196***	0.496***
	(0.0661)	(0.0461)	(0.0491)	(0.119)
Observations	422	411	420	422
R-squared	0.100	0.101	0.106	0.077
IGE Daughters:	0.347***	0.143**	0.167***	0.534***
	(0.0776)	(0.0575)	(0.0589)	(0.162)
Observations	240	234	241	240
R-squared	0.132	0.104	0.107	0.115
IGE Sons:	0.185*	0.194***	0.233***	0.429***
	(0.102)	(0.0620)	(0.0741)	(0.147)
Observations	182	177	179	182
R-squared	0.083	0.131	0.135	0.050
IGE Splits:	0.258***	0.190***	0.232***	0.474***
	(0.0708)	(0.0433)	(0.0492)	(0.103)
Observations	237	230	233	237
R-squared	0.154	0.184	0.190	0.122
IGE Migrants:	0.274**	0.133**	0.159**	0.567***
	(0.107)	(0.0663)	(0.0653)	(0.195)
Observations	185	181	187	185
R-squared	0.087	0.078	0.086	0.048

Robust standard errors in parentheses
Father’s age and child’s age are controlled for quadratically in all regressions
*** p<0.01, ** p<0.05, * p<0.1