Family Transfers in Rural Mexico: An Application to Risk Sharing and Labor Supply Elasticity

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Abstract

This paper presents a model of labor supply and consumption in a family where adult children support their retired parents. Such a family arrangement is common throughout the developing world. I show that this family arrangement creates complete risk sharing within the family. Within a family, children's wages vary exogenously. These wage shocks determine both potential income and the price of leisure for each child. The model yields three testable predictions. Compared to their low wage siblings, children with high wages (1) send more money home to support the retired parents, (2) work more hours, and (3) consume more substitutes and fewer complements for leisure. These predictions for families that share risk are very different from the predicted behavior for families that do not share risk.

I develop two novel instruments for wages: school calendar during childhood and weather during childhood. I then apply my instruments to data taken from the 1970 and 2000 Mexican Census. Empirical results are consistent with all three predictions: (1) children who receive an exogenous wage increase of 10% send home enough transfers to increase their parent's consumption by 6%; (2) men who receive an exogenous wage increase of 10% during childhood work 4% more hours throughout their lives; and (3) men who receive an exogenous wage increase of 10% own 2%-4% more cars (substitute for leisure), own 2%-3% fewer televisions (complement for leisure), and consume the same quality of food (separable from leisure).

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Introduction

People in the developing world face a great deal of income risk. Crops can fail if the rains come too early or too late (Duflo and Udry 2004). Even if the weather is favorable a farmer might become sick and unable to work (Gertler and Gruber 2002). Children who are forced to leave school early earn lower wages throughout their life (Jacoby and Skoufias 1997). There is a rich economics literature studying how individuals smooth consumption in response to short-term non-labor income shocks (Townsend 1994). However, to my knowledge, there is no research studying how individuals smooth consumption in response to long-term wage shocks. Unlike non-labor income shocks, wage shocks change both potential income and the price of leisure. Therefore, they cannot be analyzed using the tools given by the earlier literature. This paper aims to fill that gap.

In this paper, I present a model of labor supply and consumption when adult children support retired parents and children's wages vary exogenously. Following Warr (1983) a Cournot-Nash set-up is used to model how much each child gives to the retired parent. This model yields results similar to Becker (1981): a family shares risk completely. All children in the family receive identical marginal utility of consumption. However, unlike Becker's original paper, I vary the wages (price of leisure) among the adult children. Therefore, marginal utility of leisure is higher for children with high wages. The model yields three testable predictions: (1) compared to their low wage siblings, children with high wages send more money to support the retired parents; (2) compared to their low wage siblings, children with high wages work more hours; (3) compared to their low wage siblings, children with high wages consume more substitutes for leisure and less complements for leisure. Predictions (2) and (3) are very different from the theoretical predictions in the risk-sharing literature that focuses non-labor income shocks (Mace 1991). As I discuss later, the differences prove to be empirically important.

Prediction (2) is also very different from the labor literature that focuses wage variation without risk-sharing. In a model without risk-sharing wages have two simultaneous effects on labor supply: a) high wage men are richer, so they can afford to work less (income effect); b) high wage men face a higher opportunity cost of leisure, so they will work more holding income fixed (substitution effect). Therefore net impact of a wage increase on labor supply is theoretically ambiguous and has been empirically estimated at close to 0 (Kimball and Shapiro 2003). In contrast, within family labor supply elasticity is unambiguously positive in a model with risk-sharing. In the empirical section I estimate a within family labor supply elasticity of .4 – statistically and economically distinguishable from 0.

This paper uses data from the 1970 and 2000 Mexican Census to study families with adult children and retired parents. The Mexican Census is used because it contains high quality data on consumption and monetary transfers within the family. The model developed in this paper applies not just to Mexico, but to any other developing country. It might seem that few parents live long enough to worry about retirement. In fact, 77% of Mexicans born in 1935 survived to the legal retirement age of 65. Other developing countries have seen similar dramatic increases in life expectancy (Becker, Phillipson and Soares 2003). Only 25% of men over 65 and only 13% of women over 65 in the sample receive any retirement pensions in 2000. Therefore, many senior citizens are dependent on their adult children for support.

The primary empirical analysis of this paper focuses on testing prediction (2). This is equivalent to estimating β in the equation: $H_j = \gamma w_f + \beta(w_j - w_f) + \varepsilon_j$, where H_j is hours worked for individual j, w_f is the average family wage and (w_j - w_f) is the individual j's difference from the family average. β is within family labor supply elasticity and γ is between family labor supply elasticity. The model described earlier predicts that high wage children work much harder than their low wage siblings. In other words, within family labor supply elasticity is positive ($\beta > 0$). The model does not predict a sign or magnitude for between family labor supply elasticity (γ), but it does predict that $\beta > \gamma$.

I cannot measure β (within family labor supply elasticity) using ordinary least squares (OLS). Economists only observe individual wages (w_j) and individual labor supply (H_j), but they cannot observe average family wages (w_f) or individual taste for leisure (ε_j). A simple OLS regression of labor supply on wages is biased if $\text{Cov}(w_j, \varepsilon_j) \neq 0$ or $\text{Cov}(w_j, w_f) \neq 0$. Later in the paper, I will show that $\widehat{\beta}_{\text{OLS}}$ is heavily biased towards γ (between family labor supply elasticity) and very far from the actual value of β. Instead, instrumental variables (IV) are used. The instruments used are described below. Both of my instruments are correlated with individual wages (w_j) but not with average family wages (w_f) or taste for leisure (ε_j) Therefore, my instruments correspond to a policy experiment that exogenously raises wages for one child in the family while holding average family wages and taste for leisure fixed. This policy experiment yields an unbiased estimate of β.

I suggest two novel instruments for wages in rural Mexico. The first instrument uses school calendar changes. In some states the school calendar was temporarily cut from 9 months to 8 months. A man who misses one month of school during childhood has .08 less years of education than normal and earns .8% lower wages. The second instrument uses weather variation. Corn grows faster in warm weather (Pahlavanian and Silk 1988), so farm children are more likely to skip school and work on the farm during a heat wave. Raising average school temperatures by 1°C during childhood reduces completed schooling by .4 years and wages by 4%-6%. If these two instruments are used to estimate returns to schooling, they yield a 14% return in 1970 and a 10% return in 2000 for Mexican men. These estimates are consistent with a rich literature finding returns to schooling around 10% (Card 2001).

I then use the two instruments for wages to estimate β (within family labor supply elasticity) for adult males. I find that men who receive an exogenous wage increase of 10% work 4% more hours throughout their lives. This is equivalent to a within family labor supply elasticity of .4. In contrast, an OLS regression of labor supply on wages finds labor supply elasticity of only .07. I can easily reject the null that β=0 and β=γ. Point estimates for β are large enough to suggest an economically important amount of risk sharing within a family.

Another possible method for estimating β compares labor supply for two brothers. Labor supply for brother j is given by the equation: $H_j = \gamma w_f + \beta(w_j - w_f) + \varepsilon_j$ and labor supply for brother k is given by the equation: $H_k = \gamma w_f + \beta(w_k - w_f) + \varepsilon_k$. I can then difference their wages to get the equation: $H_j - H_k = \beta(w_j - w_k) + \varepsilon_j - \varepsilon_k$ and estimate β. The Mexican Census does not link brothers in the general sample. Therefore, I am forced to restrict the sample to brothers who are currently living together in a household.

I find that a man who earns 10% higher wages than his brother works 3%-4% more hours. I also find that within family labor supply elasticity is large in households with retired fathers. These results are consistent with the model created in the paper. Risk sharing with a household is predicted to occur only when children support a retired father. Hence, within family labor supply elasticity will be significant higher when the father is retired. Taken alone, the results from the sample of brothers should be used with caution. The wage differences used in my regression are endogenous and may be correlated with unobservable taste differences. In addition, the sample of brothers is highly selected, and may not be representative of the general population. However, both instrumental variables and the sample of brothers find very similar estimates of within family labor supply elasticity. This similarity is evidence that the two methods estimate the same underlying economic quantity.

For a final check on the model created in this paper, I also test the other predictions from the model earlier. According to prediction (1), high wage children give more transfers to their parents than their low siblings. According to prediction (3), high wage siblings consume more substitutes for leisure and fewer complements. I use the instrumental variables described earlier to test both predictions.

Empirical results are consistent with both predictions. Consistent with prediction (1), children who receive an exogenous wage increase of 10% send enough extra transfers home to increase their parents' consumption by 6%-7%. Consistent with prediction (3), men who receive an exogenous wage shock of 10% own 2%-4% more cars (because cars are much faster than walking, they are a substitute for leisure) and own 2%-3% fewer televisions (because televisions are a time intensive good used almost exclusively for leisure, they are a complement for leisure). In addition, an exogenous wage shock has no effect on consumption of expensive foods like meat or eggs. This result is consistent with research by Aguirre and Hurst (2004) finding that food consumption does not change after retirement (when leisure increases dramatically).[1] Taken together, the three consumption results are strong evidence for a model with non-separable leisure.

This paper is divided into nine parts. Part 1 reviews the literature on risk sharing in the developing world. Part 2 describes a model of consumption and labor supply when adult children support retired parents. Part 3 studies how to estimate within family labor supply elasticity and solves for two different empirical strategies: instrumental variables and family estimates. Part 4 describes the datasets used and Part 5 describes the instruments used. Part 6 then uses the instruments created to estimate labor supply elasticity within the family. Part 7 then creates and uses a sample of brothers to get a corroborating estimate for within family labor supply elasticity. Part 8 uses the instruments described earlier to estimate elasticity of consumption within the family.

[1] They find that retired households spend less money on groceries and more time on food preparation. These two changes roughly cancel out, so overall food quality is similar before and after retirement.

Finally, Part 9 uses these instruments to demonstrate that high wage children do indeed give significant transfers to their parents.

1. Risk Sharing in the Developing World

Most previous work on risk sharing assumes that wages are fixed and non-labor income is random. In that model, transfers exactly offset individual income shocks. Consumption by any given individual depends only on aggregate income for the group and not on his or her own income (Mace 1991). Because the model makes such specific predictions, it is very easy to test for complete risk sharing.

Economists who study consumption smoothing in the developing world[2] find evidence of significant risk sharing. In India, household food consumption mostly depends on average village income, not household income.[3] (Townsend 1994). In Mexico, unexpected transfers from the government to the very poor are shared within a village as a whole (Angelucci and De Georgio 2006). However, groups do not always provide full risk sharing. In Thailand, Townsend rejects full risk sharing (Townsend 1995). In Cote d'Ivoire, Duflo and Udry (2004) find that individual consumption depends on individual income, not just on total household consumption. Regardless of whether families share risk completely, their actions suggest that they place great value on whatever risk sharing exists. In India, parents intentionally marry their daughters into multiple villages in order to provide more opportunities for risk sharing (Rosenzweig and Stark 1989). In Thailand, workers migrate to minimize aggregate family income risk, rather than minimizing their own income risk (Paulson 2000).

There is some theoretical research studying risk sharing when wages are variable. Cremer and Pestieau (1998) develop a model where parents cannot observe wages or labor supply,[4] but they can observe annual earnings. In that model, transfers given by the parent to low income children function as an implicit tax on labor supply. Altruistic parents will give some help to low income children, but not as much as they would give if they could observe children's wages directly. Becker and Tomes (1976) create a model of human capital investment by parents when children's innate abilities are random. They show that expected risk sharing influences wage inequality. Parents invest more in human capital for the smartest children if they expect that high wage children will help out their less fortunate siblings. Therefore, wage inequality within the family is highest when children share risk as adults. However, their model does not directly address labor supply for adult children.

To my knowledge, there are no empirical papers investigating the relationship between wages and labor supply in families with risk sharing. The closest empirical research in the existing literature studies within-person labor supply elasticity over time. In Appendix 1, I show that the problem of risk sharing within a family maps closely to the problem of consumption-smoothing over the lifecycle. Both models change wages while holding the marginal utility of consumption fixed. I then discuss empirical results for the lifecycle research.

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[2] In the United States, Altonji, Hayashi and Kotlikoff (1992 and 1997) find very little risk sharing.
[3] This is after controlling for family fixed effects and focusing only on short-term income shocks.
[4] They use ability rather than wages and effort rather than hours worked, but the models are equivalent.

2. A Model of Transfers Within Extended families

Suppose that there are n adult children in a family, and one retired parent.[5] The typical family size in rural Mexico is around 6-7 children[6] – but the model works for any family with at least two children. In my empirical analysis, I focus on men because their labor supply is easier to observe. Therefore, I use 'he', 'father' and 'brother' throughout the discussion. The average wage for all individuals in the family is w_f, and child j receives an individual specific wage shock, $(w_j - w_f)$. In total, wages for child j are $w_j = w_f + (w_j - w_f)$. In the empirical section of the paper, I use education as a proxy for wages. Child j earns more than his brothers if he has more education, and less than his brothers if he has less education.

In my model there are m normal consumption goods, $(c^1, ..., c^m)$ and one normal leisure good, L. I do not assume that consumption is separable from leisure – some goods may be complements for leisure and other goods may be substitutes for leisure. Child j has three decisions to make: a) how much money to send home to support his parent, t_j; b) how much leisure, L_j, to allow himself; and c) how much to buy of each consumption good, $(c_j^1, ..., c_j^m)$. For simplicity, I assume that each person has 1 unit of time to divide between leisure and work. The model presented here has only one period so there are no savings. Child j either gives his money to the parent or spends it on his own consumption.

Every child is altruistic (α) towards the parent, so consumption by the parent is a public good for all of the adult children. This causes a free-rider problem for the family as a whole. For child j, the best possible outcome occurs when he gives little to the parent – but his brothers give as much as possible. Every other child feels the same. In this paper, I use a non-cooperative Cournot-Nash set-up to solve for transfers[7] (Warr 1983). In this set-up each child simultaneously sends a cash transfer to the parent. Because the transfers are simultaneous the actual amount given by child j is unobservable to his siblings and has absolutely no effect on their behavior. The solution to this model is a single Nash equilibrium: child j gives money until he gets the same utility from a dollar in his own pocket and a dollar in his parent's pocket. This non-cooperative equilibrium gives far too little money to the parent. Even putting the parent's utility aside, each child in the family would be strictly better off if they could cooperate to give more money. However, the Nash equilibrium is stable – no individual child benefits from giving more money to the parent.

We can write child j's maximization problem as:

[5]An alternative interpretation of this model is that the group consists of n villagers and 1 village public good. In rural Mexico, it is common for rich villagers to provide extremely expensive public goods such as communal parties. Accordingly, significant risk sharing may occur within the village (Cancian 1965). Labor supply and consumption results will be identical in this interpretation.

[6] This is estimated total fertility rate up to 1970. After 1970, fertility fell rapidly and is now a little more than 2 children per woman. The average number of siblings per adult is slightly higher, because large families are over-weighted in the next generation.

[7] Results are qualitatively similar if I use a model the family using a Stackelberg set-up (Varian 1994), or assume that the family is controlled by a single altruistic head (Becker 1981).

Max $U_j = u(c_j^1,...,c_j^m, L_j) + \alpha u(c_p^1,...,c_p^m, L_p),$ subject to:

Child j's budget constraint: $\sum_{i=1}^{m} c_j^i = w_j(1-L_j) - t_j$

Parent's budget constraint: $\sum_{i=1}^{m} c_p^i = w_p(1-L_p) + t_j + \sum_{k\neq j}^{n} t_k + \mathrm{A}$

Child j views $\sum_{k\neq j}^{n} t_k$, the transfers given by his brothers and A, the parent's non-labor income (like a retirement pension) as fixed constants.

Instead, child j focuses on changing t_j, L_j, L_p, $(c_j^1,...,c_j^m)$ and $(c_p^1,...,c_p^m)$

We can then solve to get first order conditions for child j:

$$(\partial u/\partial c_j^r) = (1/w_j)(\partial u/\partial L_j) = \lambda_j \text{ for any good r}$$
$$(\partial u/\partial c_p^s) = (1/w_p)(\partial u/\partial L_p) = \lambda_p \text{ for any good s}$$
$$\lambda_j \geq \alpha\lambda_p$$

We can also solve this maximization problem to get similar first order conditions for child k.

In this paper, I will focus on two possible regions to the solution: $\lambda_j > \alpha\lambda_p$ & $\lambda_k > \alpha\lambda_p$ and $\lambda_j = \alpha\lambda_p$ & $\lambda_k = \alpha\lambda_p$.[8] a) $\lambda_j > \alpha\lambda_p$ & $\lambda_k > \alpha\lambda_p$ In this region the family is at a corner solution. Children j and k would like to give a negative transfer to (take money from) the parent, but they cannot. Instead, they both pick a transfer of 0, the minimum transfer permitted. At the corner solution there is no risk sharing within the family. Accordingly, wages for child k have no effect on labor supply or consumption for child j. b) $\lambda_j = \alpha\lambda_p$ & $\lambda_k = \alpha\lambda_p$ In this region the family is at an interior solution. Both child j and child k give a positive transfer to the parent. At the interior solution the family shares risk completely. Therefore, child j is richer (consumes more and works less) when child k earns a high wage.

When is the family at an interior solution? Child j gives transfers to the parent when $(w_j - w_p)$ and α are large. In other words, child j gives transfers when he is rich enough to be able to do so and is altruistic enough to want to do so. In this paper, I will focus on variation in $(w_j - w_p)$ and assume that α is relatively stable[9]. Therefore, we will observe risk sharing in families where the father has much lower income than his children. When is the family at a corner solution? The most common reason is that the

[8] It is also possible that some children may be at a corner solution, and some children at an interior solution. This scenario produces qualitatively similar results.

[9] I find evidence that men who do not live in their birth state have less access to risk sharing than non-movers. This suggests that men who move are less altruistic towards their parents, and therefore less likely to be at the interior solution with risk-sharing. I cannot determine whether a low α causes men to move, or moving causes a low α.

father is able to work and earns a good wage. In that case, he can easily support himself without any help from his children.

In Appendix 2 and 3, I solve the model to get first and second order conditions at the non-cooperative Nash equilibrium. I then derive comparative statics for transfers, consumption and labor supply among the children as we change wages for child k.[10] I show that the no transfer region and the positive transfer region produce very different predictions for labor supply and consumption.

The predictions in Appendix 2 and Appendix 3 are not unique to a model of children supporting their parent. A model where an altruistic father supports his children (Becker 1981) produces similar predictions. However, the two models assume very different income distributions.[11] In Becker's model, the father is much richer than his children. This assumption is most plausible for families with children too young to work. In my model, children are much richer than their parents. This assumption is most plausible for families with adult children and parents too old to work. Later in the paper, I will present empirical data showing that more risk sharing occurs in families with retired fathers. These results are consistent with my assumption that children support parents and not vice versa.

A. Within Family Labor Supply Elasticity

Lemma 1 (No Transfer Region): $\partial(L_k - L_j)/\partial w_k$ is ambiguous

This lemma states that w_k has an ambiguous effect on relative labor supply, $(L_k - L_j)$. In other words, high wage men may work more or less than the rest of the family.

In Appendix 2, I show that $\partial L_j / \partial w_k = 0$ if there are no transfers within the family. Therefore, Lemma 1 (No transfer Solution) is equivalent to claiming that $(\partial L_k / \partial w_k)$ is ambiguous. The ambiguity occurs because two opposing forces operate: a) raising child k's wage increases his potential income, thus making him richer; b) when child k's wage increases, the opportunity cost of not working is larger. Holding wages fixed, child k works less when his potential income increases (income effect). Holding income fixed, child k works more when the price of his leisure is higher (substitution effect). The net impact of these two opposing forces is theoretically ambiguous. In practice the two effects cancel out, so I predict that increasing wages for child k has little effect on his labor supply (Kimball and Shapiro 2003).

In the model described earlier there are no transfers between families. Therefore, raising w_f has two separate effects on average family labor supply for: income effect and substitution effect. Accordingly, $\partial(L_k - L_j)/\partial w_k = \partial L_k / \partial w_f$ for families that do not share risk.

[10] My model also makes strong predictions about parents and children – not just pairs of siblings. However, I focus on sibling pairs for two reasons: 1) sibling relationships are symmetrical, making them easier to analyze theoretically; 2) because parents pay for their children's education, parental earnings and wages can have a direct impact on children's adult wages. The empirical analysis is, therefore, more complicated.

[11] Assuming that the altruism coefficient (α) is less than 1.

Lemma 1(Positive Transfer Region): $\partial(L_k - L_j)/\partial w_k < 0$

This lemma states that w_k always increases relative labor supply, $(L_k - L_j)$. In other words, high wage men always work more than the rest of the family.

In Appendix 3, I show that marginal utility of consumption is always identical for brother j and k. An increase in w_k has no effect on relative income, and the income effect does not affect labor supply. Instead, within family labor supply elasticity is determined only by the substitution effect. The substitution effect is always positive, so high wage brothers always work more than low wage brothers.

In the model described earlier there are no transfers between families. Therefore, raising w_f has two separate effects on average family labor supply for: income effect and substitution effect. Accordingly, $\partial(L_k - L_j)/\partial w_k < \partial L_k/\partial w_f$ for families that share risk. In the empirical section, I will show not only that $\partial(L_k - L_j)/\partial w_k < 0$, but also $\partial(L_k - L_j)/\partial w_k < \partial L_k/\partial w_f$. This second result provides strong evidence for risk sharing within a family.

These predictions about within family labor supply elasticity are original to my model of risk sharing with random wages. In a model with random non-labor income we will never observe men who receive positive income shocks working more. By assumption, leisure is a normal good, so high income men will always consume more leisure (work less). If there are no transfers within the family, a man who wins the lottery is richer than his less lucky brothers and consumes more leisure. If families share risk completely, then a man who wins the lottery has the exact same final income as his less lucky brothers and consumes the exact same amount of leisure. The difference between the two predictions is driven by price changes. A wage increase for brother k not only raises his potential income – it also increases the opportunity cost of leisure. Therefore, brother k will work more in a family with complete risk sharing.

B. Within family Consumption Elasticity

Lemma 2 (No Transfers Region): $\partial\left(\sum_{r=1}^{m} c_k^r - c_j^r\right)/\partial w_k > 0$

This lemma states that w_k unambiguously increases relative consumption, $\sum_{r=1}^{m} c_k^r - c_j^r$. In other words, high wage men always consume more than the rest of the family.

In Appendix 2, I show that $(\partial c_j^r/\partial w_k) = 0$ for any good r if there are no transfers within the family. Therefore, Lemma 2 (No transfer Solution) is equivalent to claiming that $\partial\left(\sum_{r=1}^{m} c_k^r\right)/\partial w_k > 0$. This increase in consumption occurs because there are no savings or transfers to parent. When child k's wage rises he keeps all of his extra earnings for himself. By assumption, consumption is normal – so child k will spend some of his extra money purchasing more consumption goods. It is also likely that $(\partial c_k^r / \partial w_k) > 0$ for any good r, but that is not required by the model.[12]

Lemma2 (Positive Transfers Region):

$$\partial\left(c_k^r - c_j^r\right)/\partial w_k < 0 \text{ if } (\partial u^2 / \partial c^r \partial L) > 0$$

$$\partial\left(c_k^r - c_j^r\right)/\partial w_k > 0 \text{ if } (\partial u^2 / \partial c^r \partial L) < 0$$

This lemma states that w_k has an ambiguous effect on relative consumption, $(c_k^r - c_j^r)$. In other words, high wage men consume more substitutes for leisure and less complements for leisure than the rest of the family.

In Appendix 3, I show that all brothers receive the same marginal utility of consumption. If labor supply was fixed all brothers would consume the exact same bundle of consumption goods. However, labor supply varies within the family: brothers with high wages work more hours. By assumption, men working long hours consume more substitutes to leisure and fewer complements to leisure (holding income fixed). Therefore, high wage men will consume more substitutes for leisure and fewer complements relative to their low wage brothers.

These predictions about within family elasticity of consumption are also novel and testable. In a model with random non-labor income we will never observe men with positive income shocks consuming less of any good. By assumption, all consumption goods are normal, so high income men always consume more of any good. If there are no transfers within the family, a man who wins the lottery is richer than his less lucky brothers and consumes more. If families share risk completely, then a man who wins the lottery has the exact same final income as his less lucky brothers and consumes the exact same consumption bundle. Results are similar in a model of random wages and separable consumption. Later in the paper, I will show that high wage men own fewer televisions (complement to leisure) than their low wage brothers. These empirical results are strong evidence for risk sharing within the family and non-separable consumption.

3. How to Estimate Within Family Labor Supply Elasticity

Suppose that the true relationship between hours worked, *H*, and wages is determined by the equation:

$$H_j = \gamma_j w_f + \beta_j (w_j - w_f) + \varepsilon_j$$

As discussed in section 2, w_f is average wages for family as a whole and w_j is individual j's wage. The error term ε_j represents individual j's unobservable taste for leisure; γ_j (between-family labor supply elasticity) is a random variable drawn from the distribution γ; and β_j (within family labor supply elasticity) is a random variable drawn from the distribution β. I will assume that γ_j and β_j are independent of w_f and $(w_j - w_f)$.

[12]The discrepancy is only possible if labor supply elasticity is not 0. If labor supply elasticity is positive, high wage men may consume less complements for leisure. Conversely, if labor supply elasticity is negative, high wage men may consume less substitutes for leisure.

In this paper, I focus on estimating the distribution of β and comparing β to γ. In a population without family risk sharing $\mathrm{E}(\gamma_j) = \mathrm{E}(\beta_j)$. In a population where families share risk $\mathrm{E}(\gamma_j) < \mathrm{E}(\beta_j)$. In my empirical analysis, I test the null hypothesis that $\mathrm{E}(\gamma_j) = \mathrm{E}(\beta_j)$. In order to reject the null hypothesis, I do not need a population where every families shares risk completely, I need only a population with a significant fraction of families that share risk. For an additional check on my model, I use similar techniques to estimate the within family elasticity of consumption and the within family elasticity of transfers.

Method 1: OLS

In the Mexican Census, wages for men and their household are easily observable – but there is no information on wages for brothers living outside the household. Therefore, I cannot observe w_f (average family wages) for the general population. Suppose that I regress H_j (hours worked) on w_j (own wages) without controlling for w_f and ε_j. This is equivalent to an OLS regression of H_j on w_j. If the sample size is sufficiently large, our estimates converge to the population analogues.

$$\widehat{\beta}_{OLS} = \mathrm{Cov}(H_j, w_j) / \mathrm{Var}(w_j) = \mathrm{Cov}\left(\gamma_j w_f + \beta_j (w_j - w_f) + \varepsilon_j, w_f + (w_j - w_f)\right) / \mathrm{Var}(w_j)$$

By assumption, γ_j and β_j are independent of w_f and (w_j - w_f). And by construction, w_f and $(w_j - w_f)$ are uncorrelated. We can therefore simplify the expression above to get:

$$\begin{aligned}
&\widehat{\beta}_{\mathrm{OLS}} = \mathrm{Cov}\left(\gamma_j w_f + \beta_j (w_j - w_f) + \varepsilon_j, w_f + (w_j - w_f)\right) / \mathrm{Var}\left(w_j\right) = \\
&\left(\mathrm{Cov}(\gamma_j w_f, w_f) + \mathrm{Cov}\left(\beta_j (w_j - w_f), (w_j - w_f)\right) + \mathrm{Cov}(\varepsilon_j, w_j)\right) / \mathrm{Var}\left(w_j\right) = \\
&\left(\mathrm{E}(\gamma_j)\mathrm{Var}(w_f) + \mathrm{E}(\beta_j)\mathrm{Var}(w_j - w_f) + \mathrm{Cov}(\varepsilon_j, w_j)\right) / \mathrm{Var}\left(w_j\right)
\end{aligned}$$

This OLS estimate is unsatisfactory for two main reasons[13]: a) Wage (w_j)may be correlated with the unobservable error term (ε_{j}). For example, men who earn high wages might be healthier. This would bias the labor supply elasticity upwards (chronically ill men need more leisure). b) Even if $\mathrm{Cov}(\varepsilon_j, w_j) = 0$, we still cannot recover $\mathrm{E}(\beta_{\mathrm{j}})$ with OLS. Instead OLS estimates a weighted average of $\mathrm{E}(\gamma_{\mathrm{j}})$ (between family labor supply elasticity) and $\mathrm{E}(\beta_{\mathrm{j}})$ (within family labor supply elasticity). If $\mathrm{Var}(w_f)$ is large then $\widehat{\beta}_{\mathrm{OLS}}$ is close to $\mathrm{E}(\gamma_j)$, and if $\mathrm{Var}(w_j - w_f)$ is large then $\widehat{\beta}_{\mathrm{OLS}}$ is close to $\mathrm{E}(\beta_{\mathrm{j}})$. In section 2, I showed that $\mathrm{E}(\gamma_j) \le \mathrm{E}(\beta_j)$ so $\mathrm{E}(\gamma_j) \le \widehat{\beta}_{\mathrm{OLS}} \le \mathrm{E}(\beta_j)$ for all populations. These results are very similar to Mundlak (1978).

[13] Another problem is that OLS provides only a single number – not the full distribution of β.

Method 2: Instrumental Variables (IV)

Suppose we have an instrument Z such that $\text{Cov}(Z_j, w_f) = 0$, $\text{Cov}(Z_j, \varepsilon_j) = 0$ & $\text{Cov}(Z_j, w_j - w_f) \neq 0$. In other words, Z is only correlated with individual wages, and not with family background or unobservable error terms. Then Z is an instrument for $(w_j - w_f)$ alone. We can use Z as an instrument for wages, and recover β alone. If the sample size is sufficiently large, our estimates converge to the population analogues.

$$\widehat{\beta}_{IV} = \text{Cov}(H_j, Z_j) / \text{Cov}(w_j, Z_j) =$$
$$\text{Cov}(\gamma_j w_f + \beta_j (w_j - w_f) + \varepsilon_j, Z_j) / \text{Cov}(w_f + (w_j - w_f), Z_j) =$$
$$\left(\int_{-\infty}^{\infty} \beta_x P(\beta_j = \beta_x) \text{Cov}((w_j - w_f), Z \big| \beta_j = \beta_x) \right) / \text{Cov}((w_j - w_f), Z_j)$$
$$\widehat{\beta}_{\text{IV}} = E(\beta_j) \text{ only when } \text{Cov}((w_j - w_f), Z \big| \beta_j = \beta_x) \text{ is constant}$$

Therefore, instrumental variables provide an estimate only of β (within family labor supply elasticity), but not of γ (between-family labor supply elasticity). And because Z is not correlated with ε, $\widehat{\beta}_{\text{IV}}$ is an unbiased estimate of β. We can use IV to create a policy experiment: exogenously raise wages for one child, but hold wages for the rest of the family fixed. However, IV still cannot recover the complete distribution of β. $\widehat{\beta}_{\text{IV}}$ is a weighted average of the various β_{j}'s, with the weights determined by how much Z affects $(w_j - w_f)$ [14] (Heckman, et al 2006).

In this paper, I use two instruments for schooling: local weather and local school calendar from ages 6-17. These instruments are described in more detail later in the paper. Both of these instruments primarily affect children on the margin for dropping out of school before they are 17. Therefore, the instruments measure the effect of primary school and secondary school on adult behavior but say little about the effect of college and graduate school[15]. In addition, both instruments have the largest impact on children from moderate income rural communities – children in very poor rural areas almost never go to school, and children in rich urban areas are unlikely to drop out of school before graduation. As a result, $\widehat{\beta}_{\text{IV}}$ primarily estimates within family labor supply elasticity for those communities.

It is also possible that $\widehat{\beta}_{\text{IV}}$ over-samples families with more risk sharing than average. Becker and Tomes (1976) predict that families that share risk have a more elastic demand for schooling. Both of my instruments work by slightly changing the opportunity cost of schooling. This change in opportunity cost has a large effect on groups with elastic demand for schooling, and a small effect on groups with an inelastic

[14] In theory, we could use a large number of instruments to recover the full distribution of β. However, it is very difficult to find enough valid instruments.

[15] The instruments have a statistically significant (if small) effect on college enrollment.

demand for schooling. Therefore, $\text{Cov}\left((w_j - w_f), Z_j\right)$ is large when families share risk and $\text{Cov}\left((w_j - w_f), Z_j\right)$ is small when families do not. As a result, $\widehat{\beta}_{\text{IV}}$ primarily estimates within family labor supply elasticity for families with significant amounts of risk sharing, and is not necessarily representative of the general population.

In the empirical sections of the paper, I will focus on testing the null hypothesis that $\widehat{\beta}_{\text{OLS}} = \widehat{\beta}_{\text{IV}}$. Earlier in this section, I showed that $\text{E}(\gamma_j) \le \widehat{\beta}_{\text{OLS}} \le \text{E}(\beta_j)$ and $\text{E}(\beta_j) \approx \widehat{\beta}_{\text{IV}}$. Therefore, a result that $\widehat{\beta}_{\text{OLS}} < \widehat{\beta}_{\text{IV}}$ is equivalent to showing that $\text{E}(\gamma_j) < \text{E}(\beta_j)$ and rejecting the null that $\text{E}(\gamma_j) = \text{E}(\beta_j)$. Using a sample of brothers who share a household, I calculate that $\left(\text{Var}(w_f) / \text{Var}(w_j)\right)$ is more than .75[16] in rural Mexico. Accordingly, $\widehat{\beta}_{\text{OLS}}$ is heavily biased towards $\text{E}(\gamma_j)$, and $\left(\widehat{\beta}_{\text{IV}} - \widehat{\beta}_{\text{OLS}}\right)$ is not much smaller than $\left(\text{E}(\beta_{\text{j}}) - \text{E}(\gamma_{\text{j}})\right)$. Theoretical results are similar if I use OLS and IV to measure within family elasticity of consumption.

Method 3: Within family Estimates

Suppose that we observe two brothers in a household. Brother j has wages w_j, and brother k has wages w_k. We can write labor supply equations for the two brothers as:

$$H_j = \gamma_j w_f + \beta_j (w_j - w_f) + \varepsilon_j \text{ \& } H_k = \gamma_k w_f + \beta_k (w_k - w_f) + \varepsilon_k$$

Because the two brothers are from the same family, they both have the exact same w_f (average family wages). I can difference their H's to get the equation:

$$H_j - H_k = \gamma_j w_f + \beta_j (w_j - w_f) - \gamma_k w_f - \beta_k (w_k - w_f) + \varepsilon_j - \varepsilon_k \rightarrow$$
$$H_j - H_k = (\gamma_j - \gamma_k) w_f + \beta_j (w_j - w_k) + (\beta_k + \beta_j)(w_k - w_f) + (\varepsilon_j - \varepsilon_k)$$

We can then regress $H_j - H_k$ on $w_j - w_k$ to estimate β.

$$\widehat{\beta}_F = \text{Cov}(H_j - H_k, w_j - w_k) / \text{Var}(w_j - w_k) =$$
$$\text{Cov}\left((\gamma_j - \gamma_k) w_f + \beta_j (w_j - w_k) + (\beta_k + \beta_j)(w_k - w_f) + \varepsilon_j - \varepsilon_k, w_j - w_k\right) / \text{Var}(w_j - w_k)$$

By assumption, γ_j, γ_k, β_j, β_k and w_f are uncorrelated with w_j and w_k. So, we can simplify to get:

[16].My calculation does not account for measurement error in wages, so the true correlation may be even higher. This is a highly selected sample, and may not be representative of the general Mexican population.

$$\widehat{\beta}_F = \text{Cov}((\beta_j - \beta_k)(w_j - w_k) + \varepsilon_j - \varepsilon_k, (w_j - w_k)) / \text{Var}(w_j - w_k) =$$
$$.5*\text{E}(\beta_j + \beta_k) + \left(\text{Cov}(\varepsilon_j - \varepsilon_k, w_j - w_k) / \text{Var}(w_j - w_k)\right)$$

Therefore, a family regression estimates β only, not γ. We can use family data to observe what happens when one brother earns a higher wage than the second brother.

In the empirical section of the paper, I will focus on testing the null hypothesis that $\widehat{\beta}_{\text{OLS}} = \widehat{\beta}_{\text{F}}$. As argued earlier with IV, a result $\widehat{\beta}_{\text{OLS}} < \widehat{\beta}_{\text{F}}$ is equivalent to showing that $\text{E}(\gamma_j) < \text{E}(\beta_j)$. However, this within family regression should be used with caution. Unlike the instrumental variables estimate, I use endogenous wage differences. Therefore, results may be biased if high wage men have different tastes for work than their low wage brothers. In addition, families with two sons living at home are relatively rare and may not be representative of the general population. I discuss this sample selection problem in more detail later in the paper.

In section 7, I will use within family regressions to estimate a distribution for β, not just a single point like the IV and OLS estimates. Because parental characteristics are observed, I can split the sample into various subgroups. In particular, I can test whether risk sharing varies with the parent's financial needs. My model suggests that children support retired parents but not working parents. Therefore, siblings with retired parents share risk, leading to high labor supply elasticity. In contrast, siblings with working parents do not share risk, leading to low labor supply elasticity. Empirical results are consistent with this prediction.

4. Data Sets Used

The main datasets used in this paper are taken from the 1970 and 2000 Mexican Census. In addition, I also used the 1960 and 1990 Census for background information. The 1980 Census is not publicly available, so I was unable to include it in my analysis. In the 2000 Mexican Census dataset rural residents are over-sampled. I correct for this over-sampling using the sampling weights given by the Census. Results are very similar if I do not weight observations at all.

In my analysis, I use all men 25-74 born outside of Mexico City who report valid data. I restrict the sample to men to minimize the importance of household production and selection into the labor market. I also exclude men under 25 because they are still investing in their human capital and exclude men over 74 because most of them are retired. The final exclusion is of men born in Mexico City. Both of my instruments only affect education for boys in rural areas, and are not valid instruments for men born in Mexico City.[17] If a man born in rural areas later moves to Mexico City he remains in the sample. Demographics for the sample are given in Tables 1 and 2.

Even though the Mexican Census surveys all residents of Mexico, sample selection is still a serious problem. In 2000, approximately 10% of all adults born in Mexico currently live in the United States (Lacuesta 2004). These emigrants are lost to

[17] In fact, an instrument that decreases schooling in rural Mexico slightly increases schooling in Mexico City.

the sample. In Appendix 4 I discuss how emigrants differ from the rest of the population. However, emigration cannot explain the empirical results. There was very little emigration in 1970 but I find similar labor supply elasticity in 1970 and 2000. In addition, results for transfers received are similar when I focus on transfers received from family in Mexico, excluding transfers from family in the United States.

I limit my empirical research to wage variation caused by education shocks. A child who drops out of school before learning to read is almost certain to earn far less than his brother who completes primary school. Therefore, education can be used as a proxy for wages.[18] In addition, increasing education is also an important policy goal in its own right. In rural Mexico schooling is viewed as optional, and children often drop out to help on the farm. The Mexican government recently introduced a new welfare program explicitly designed to encourage rural children to stay in school (Schultz 2001). My model suggests that this new program has enormous benefits to rural communities and that the parents benefit at least as much as their children.

Using education shocks also avoids a number of difficult econometric problems. The Mexican Census asks about hours worked and monthly earnings, but not directly about wages. Economists can then calculate wages = (earnings/hours worked) but this calculation presents problems of its own. If hours are measured with error, then wages are also measured with error (Bound, Brown, Duncan and Rodgers 1991). In addition, wages are not observable for men not working. An econometrician studying labor supply must impute wages for these men or drop them from the sample. There is a rich literature studying various statistical techniques to impute wages, and discussing potential problems with each technique (Hirsch and Schumacher 2004). I can avoid the problems of measurement error and imputation by using education as an instrument for wages[19]. Education is observed for all men in the sample[20], regardless of labor force participation. This procedure provides a consistent estimate of labor supply elasticity even if education is measured with error[21] (Ashenfelter and Krueger 1994). In my empirical work, I regress outcome variables directly on education, but still report results as if I had used education as an instrument for wages.[22]

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[18] If education changes preferences, then the IV point estimates are biased. However, I can still test the hypothesis of risk sharing within the family. Both IV and OLS are affected identically by preference changes, so (IV-OLS) measures risk sharing.

[19] In order to use education as an instrument I assume that schooling is not correlated with labor supply when wages are held fixed.

[20] About 3% of men in the Mexican Census do not report education, these men are dropped from the sample.

[21] Assuming that returns to education are measured correctly. It is possible that selection into the labor market biases returns to education downward. This would occur if men who select out of the labor force would have received lower wages than the rest of the sample, and high education men are more likely to work (as hypothesized in my paper). In this case point estimates for labor supply elasticity are biased upwards slightly. However, I will not wrongly reject the null hypothesis that labor supply elasticity is 0. In fact, I find that correcting for selection into the labor market has little effect on returns to education in rural Mexico.

[22] For simplicity, I will use a 10% return to education in 2000 and a 15% in 1970. Returns to schooling estimates are presented later in the paper, in tables 4, 8 and 9.

5. Two Novel Instruments for Education & Wages

The first instrument for education was created by changes in the school calendar during the 1960's. Originally, Mexico had two separate school calendars. The temperate states[23] followed calendar "Type A", with a school year starting at the end of January and continuing until the end of November. The tropical[24] states followed calendar "Type B", with a school year starting at the beginning of September and continuing until the end of June the next year. In 1965, the government decided to merge the two calendars by shortening the Type A school year by one month for the next 5 years. Therefore, "Type A" states had school from late January to late October in 1966, late December to late September in 1967, late November to late August in 1968, late October to late July in 1969 and late September to late June in 1970. After 1970, all states started school in early September, and continued until the end of June. In other words, temperate states had a short school year between 1965 and 1970 and a normal school year for the rest of time. The tropical states never had their school calendar touched, so they had a normal school year throughout.

Why did the school calendar change? According to the Education Bureau's reports, the main motive was to allow teachers and students to move across states with less disruption. They believed that students who changed from one school calendar to another had a lot of difficulty adjusting[25]. There is no hint in the news reports that the school calendar change was prompted by any problems with Type A or Type B schools. I assume that the calendar change was an exogenous shock to education, uncorrelated with family background or economic conditions.

Children in states with a shorter school calendar suffered huge decreases in schooling. Between 1965 and 1966, grade repetition in primary schools increased from 20% to 25% and rural drop-out rates increased from 20% to 25%.[26] Many children were simply unable to learn the required amount of material in 8 months rather than 9.[27] Results are similar if I look at completed education for adult men. In Figure 1, I compare average schooling for temperate and tropical states by year of birth. Eyeballing the data[28], we can see that men born in tropical states get more completed schooling when they are offered more school. In Table 3, I find similar results with a regression that

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[23] Chiapas, Distrito Federal (Mexico City), Guanajuato, Hidalgo, Mexico state, Michoacan, Morelos, Oaxaca, Puebla, Queretaro, San Luis Potosi, Tabasco, Tlaxcala, Veracruz. Many of these states are actually further south than some 'tropical states', but they are high altitude (and so cool).

[24] Aguascalientes, Baja California Norte, Baja California Sur, Campeche, Coahuila, Colima, Chihuahua, Durango, Guerrero, Jalisco, Nayarit, Nuevo Leon, Quintana Roo, Region Lagunera, Sinaloa, Sonora, Tamaulipas, Yucatan and Zacatecas

[25] In fact, I find no evidence that the calendar change actually helped students who moved.

[26] This is for children in primary schools in temperate states not including Mexico City from 1965 to 1966. I was not able to obtain the same numbers for tropical states, but I have no reason to believe that they changed significantly from 1965 to 1966. The education statistics give negative drop-out rates for urban areas in both years.

[27] These results are very different from Pischke (2003), who found that German children in the 1960s were able to handle a shortened school year without significant problems.

[28] The data also suggest that men born between 1940 and 1950 were also affected, even though they were too old to be in school between 1965 and 1970. This is likely caused by measurement error for age – some men who claim to be 60 are only 50.

controls for state of birth and year of birth. One month of missed school reduces completed education by .07 to .09 years.

Children who lost education from the school calendar changes earn lower wages throughout their adult life. In Table 4, I estimate the returns to schooling, using school calendar as an instrument. I find that one year of education increases wages by 10%. Therefore, one month of missed schooling reduces adult wages by .7%-.9%. I can use school calendar changes as an instrument for wages to estimate within family labor supply elasticity.

The second instrument for wages uses changes in the timing of demand for farm labor. In rural Mexico children often miss school when they are needed on the farm. Therefore, children attend more school if peak farm labor demand happens to fall during the school vacation, and less school if peak farm labor demand coincides with the academic year. It might seem that communities could avoid this problem by changing the school calendar so that vacations always coincide with peak farm labor demand. However, the Mexican school calendar is centrally planned and cannot be adjusted to match local agricultural needs. Hence, random variation in the timing of demand for farm labor has a long-term impact on the amount of schooling completed.

I use weather to exogenously change the timing of demand for farm labor. Crops grow faster in warmer temperatures (Pahlavanian and Silk 1988) (Pastenes and Horton 1996). For example, Figure 2 shows that corn grows three times faster at 29°C (84°F) compared to 16°C (60°F). In addition, insects and other pests also grow faster in warm temperatures (Trudgill, Honek, Li and Van Straalan 2005). The faster growth rate in warm months creates an increased demand for weeding, pest control and eventually harvesting. Therefore, the demand for farm labor is higher in warm months and rural children are more likely to miss school when temperatures are warm. The effect of temperature on school attendance is quite large. In Table 5, I use the 1970, 1990 and 2000 Census to test for the impact of weather on current school attendance. I find that boys are .7-1.3% less likely to be in school when mean temperature last month was 1° Celsius warmer.

It might seem that weather affects adults as well as children, thus disqualifying weather as an instrument for education. For example, warm weather might increase total farming profits (Lang 2001) or increase mortality (Ballester, Corella, Perez-Hoyos, Saez and Hervas 1997). In order to control for the effect of weather on adults, I do not use mean temperature as an instrument for education. Instead, I use Δ Temp= Mean School Temp – Mean Vacation Temp as an instrument for education. Δ Temp[29] is positive if a heat wave occurs during the academic year and Δ Temp is negative if a heat wave occurs during the school vacation. Because adults do not attend school, they have no reason to care about the timing of a heat wave with regards to the school calendar. So, Δ Temp is uncorrelated with farming profits or mortality. In contrast, Δ Temp is highly correlated with completed education: children get less schooling only if a heat wave occurs during the academic year.[30]

[29] Δ Temp is positively with the number of months of school missed. This will result in point estimates for the Weather IV and the Calendar IV quite close. Results remain qualitatively similar if I control for the correlation.

[30] In fact, heat waves during the school vacation increase schooling, since more farm labor is completed during the school vacation, leaving less work to compete with schooling.

I find that children who experience warm temperatures in the school year get less schooling and earn lower wages. In Tables 6 and 7, I find that men get .4 less years of education when Δ Temp ages 6-17 is 1° Celsius larger. Results are similar in 1970[31] and 2000. In tables 8 and 9, I use temperature during childhood as an instrument to estimate returns to education. I find that one year of schooling increases wages by 15% in 1970 and 10% in 2000. Raising Δ Temp during childhood by 1° Celsius reduces adult wages by 4%-6%. In all regressions, I control for the average monthly temperature, so Δ Temp is not affected by changes in the school calendar or by different weather patterns across states. I also control for year of birth, so my results are not affected by long-term weather changes. Instead, only short-term weather variation drives the instrument. This weather variation is determined by global factors, and is completely exogenous to any choices made by the local community.

My analysis of the effects of weather on schooling is not unique in the economics literature. Jacoby and Skoufias (1997) find that children in India are less likely to attend school when droughts reduce family income. In Cote d'Ivoire, Jensen (2000) finds that children are less likely to attend school if rainfall is too scarce or too plentiful, and Duflo and Udry (2004) find that children are more likely to attend school when the yam crop receives favorable rainfall. However, these papers differ from mine in two important respects. First, they focus on the relationship between schooling and income, implicitly assuming that weather has no impact on the productivity of child labor. Second, they use school attendance as an end-point, rather than using the decreased education as an instrument for adult wages.

In my empirical analysis, I make two crucial assumptions: 1) both of the instruments described above are uncorrelated with individual differences in altruism and tastes; and 2) both of the instruments described above are correlated only with individual wages, and not average family wages. Therefore, my instrumental variables are equivalent to a policy experiment that raises individual wages while holding everything else fixed. The first assumption is reasonable. School calendar and weather ages 6-17 are determined only by year of birth and state of birth. Choices made by an individual or his family have no effect on the wage shock received, so it is unlikely that wage shocks are correlated with unobservable individual differences in tastes. The second assumption is less realistic. Individual wage shocks are likely to be positively correlated with average family wages. Twins always receive identical wage shocks and siblings close in age receive similar wage shocks. Even if each child did receive a completely independent wage shock, raising wages for one individual still has a non-trivial effect on average family wage. This correlation is larger in small families, and smaller in large families. Because individual wage shocks are positively correlated with average family wages, $\widehat{\beta}_{\mathrm{IV}}$ is a biased estimate of within family labor supply elasticity. However, this bias pushes $\widehat{\beta}_{\mathrm{IV}}$ closer $\widehat{\beta}_{\mathrm{OLS}}$, making it harder to reject the null. Despite this bias towards the null, I can still easily reject the null that $\widehat{\beta}_{\mathrm{IV}} = \widehat{\beta}_{\mathrm{OLS}}$. I can also reject the null that OLS = IV for television ownership and food consumption.

It might seem that this paper ignores an obvious instrument for education in Mexico: the PROGRESA program. This is a new program where the Mexican

[31] Using only the first column.

government paid rural parents to keep their children in school. PROGRESA has been shown to significantly increase school attendance (Schultz 2001). Unfortunately, the PROGRESA program is not yet a suitable instrument for adult wages because it was first introduced in 1997 (Attanasio, Meghir and Szekely 2003). Hence, most of the children affected are still in school or just starting to work at the time of the 2000 Census.

6. Within family Labor Supply Elasticity with IV

The model described in section 2 makes strong predictions about labor supply elasticity. Compared to their low wage brothers, men with high wages work much longer hours. In other words, within family labor supply elasticity is positive and much larger than 0. In this section, I use instrumental variables to estimate within family labor supply elasticity. My instruments are equivalent to a policy experiment that exogenously raises wages for one child while holding wages for the rest of the family fixed.

I estimate within family labor supply elasticity equals .4. In Table 10, I find that raising wages by 10% increases labor supply for men in 2000 by 1.5 hours per week from a mean of 40. In Table 11, I find that raising wages by 10% increases labor supply for men in 1970 by .4[32] months per year from a mean of 10. Using those coefficients, I calculate $\widehat{\beta}_{\text{IV}}$ (within family labor supply elasticity) of approximately .4 for both years. Standard errors are low enough that I can easily reject the null hypothesis that within family labor supply elasticity is 0 and the null hypothesis that $\widehat{\beta}_{\text{IV}} = \widehat{\beta}_{\text{OLS}}$.

I calculate that risk sharing within the family increases labor supply elasticity by at least .33. How do I calculate that number? Earlier in the paper, I showed that $\text{E}(\gamma_j) < \widehat{\beta}_{\text{OLS}} < \text{E}(\beta_{\text{j}})$ and $\widehat{\beta}_{\text{IV}} \approx \text{E}(\beta_{\text{j}})$. In tables 10 and 11, I find that $\widehat{\beta}_{\text{OLS}}$ is about .07. Therefore, risk sharing within the family increases labor supply elasticity by at least (.4-.07) = .33. Most of the increase in labor supply observed is the result of men switching from non-work to full-time work. Very few men in Mexico work part-time, so labor supply elasticity is small and statistically insignificant when I restrict the sample to men who participate in the labor force.

Measurement error cannot explain the difference between $\widehat{\beta}_{\text{OLS}}$ and $\widehat{\beta}_{\text{IV}}$ in Tables 10 and 11. While it is true that measurement error biases $\widehat{\beta}_{\text{OLS}}$ point estimates towards 0 (Griliches 1977), this bias is easy to correct. Compared to returns to education estimated with IV (ρ_{IV}), returns to education estimated with OLS (ρ_{OLS}) are biased downwards and the ratio ($\rho_{\text{IV}}/\rho_{\text{OLS}}$) measures the amount of measurement error (Ashenfelter and Krueger 1994). Based on Tables 4, 8 and 9, that I calculate that the downward bias for $\widehat{\beta}_{\text{OLS}}$ is only 10% in 2000 and 30% in 1970. Even after correcting for this downward bias, I still find that $\widehat{\beta}_{\text{OLS}}$ is only .1 or less. This number is both statistically and economically different from the within family labor supply elasticity of .4.

Understanding risk sharing within the family is not just theoretically important, it is also necessary in order to correctly predict the impact of policy changes. For example,

[32] Taken from column 1.

suppose that the Mexican government introduces a pilot program that gives men extra job training. After intensely studying the small group randomly selected to receive training, the government finds that the program increases wages by 10% and increases labor supply by 4%. A policy maker might look at these numbers, and conclude that extending the program to all men would dramatically increase overall employment. In fact, the 4% increase in labor supply only occurs with a small experimental program. Because the program is so small, it only raises wages for one man, while holding average family wages fixed. The policy-maker has measured within family labor supply elasticity, which is .4 (IV from tables 10 and 11). If the program was universal, then it would raise average family wages, not just individual wages. An increase in average family wages by 10% increases labor supply by at most .7%, rather than 4% (OLS from tables 10 and 11).

7. Within family Labor Supply Elasticity With Brothers

For an additional check on my model, I study within family labor supply elasticity using a sample of brothers. In the brother sample, I restrict the sample to pairs of brothers living in their parents' house in the 2000 Census. I only include a pair of brothers if both men are aged 25-74 and report valid education. If there are more than two brothers in a household, I use the oldest two brothers. Because I am focusing on rural areas, I also exclude households where either brother was born in Mexico City. Despite all of these sample restrictions, I was able to find more than 28,000 pairs of brothers[33] out of approximately 2 million men total. Results were qualitatively similar if I used pairs of brothers where one brother is head of the household, but sample sizes were smaller.

It is important to note that all of the results described above rely on endogenous wage differences between brothers. My estimates of within family labor supply elasticity may be biased if wage differences are correlated with unobservable taste differences. For example, lazy brothers might not do their homework and be forced to repeat grades in school. As adults they earn lower wages and work less – but both are caused by the underlying laziness. In addition, the sample of brothers is highly selected[34]: very few Mexican men live at home with their parents. Demographics for the sample of brothers are compared with the general population in table 12. Men living in their parents' home are much younger and much less likely to be married than average. Men living at home are also more likely to be disabled, more likely to be in school, and less likely to work. It is also possible that unobservable variables may be different for men living in their parents' home and men living in their own household. For example, it is possible that men living at home might be more altruistic than average (staying home to take care of disabled parents requires a lot of altruism), or less altruistic than average (not getting married and moving out when parents want grandchildren indicates selfishness). This sample selection could create a correlation between wages and labor supply in the sample of brothers, even if no correlation exists in the general population. And even if sample

[33] The Census does not distinguish between full brothers, half brothers and step brothers.

[34] Because both brothers are living in their parents' home they are both unrepresentative of the general population. This could increase or decrease the importance of sample selection, depending on what factors determine living arrangements.

selection does not create a false correlation, the sample of brothers may not be representative of the general population. Therefore, any labor supply elasticity results from the sample of brother may be biased and should be used with caution.

However, I can provide one piece of evidence suggesting (but not proving) that within-family labor supply elasticity from the brothers sample is relatively close to within-family labor supply elasticity for the complete population. I test for differences in labor supply elasticity between the two groups by comparing results from an OLS regression of labor supply on education for both groups. In section 5, I showed that education can be used as an instrument for wages. In Section 3, I showed that $\widehat{\beta}_{\text{OLS}} = \left(\text{E}(\gamma_j)\text{Var}(w_f) + \text{E}(\beta_j)\text{Var}(w_j - w_f) + \text{Cov}(\varepsilon_j, w_j)\right) / \text{Var}\left(w_j\right)$. If I assume that both groups have similar $\text{E}(\gamma_j)$, $\text{Var}(w_f)$, $\text{Var}(w_j - w_f)$ and $\text{Cov}(\varepsilon_j, w_j)$ - then $\widehat{\beta}_{\text{OLS}}$ will be the same for both groups if and only if $\text{E}(\beta_j)$ is the same. In other words, if every other factor is the same, then the only differences in $\widehat{\beta}_{\text{OLS}}$ between the two samples are caused by different within family labor supply elasticity. Results from the two OLS regressions are given in Table 13. I find that both samples provide a similar estimate of $\widehat{\beta}_{\text{OLS}}$[35]. This result suggests that within family labor supply elasticity ($\text{E}(\beta_j)$) is the same for both groups. Accordingly, the results for brothers living at home provide useful evidence about within family labor supply elasticity for the general population.

In this section, I focus on testing two hypothesizes: (1) compared to the low wage brother, the high wage brother works more hours; (2) in households with retired parents, labor supply elasticity is larger. I cannot test any other implications of the model created in section 2. The Mexican census does not ask about transfers within a household, so there is no way to determine how much each sibling contributes to household needs. Similarly, the only consumption data available is household based, so I cannot determine how much each brother is consuming individually.

It is relatively simple to measure labor supply elasticity in the sample of brothers sample. I simply regress $\Delta \text{ Hours}_{\text{jk}} = H_j - H_k$ on $\Delta \text{ Education}_{\text{jk}} = S_j - S_k$ and $\Delta \text{ Hours}_{\text{jk}} = H_j - H_k$ on $\Delta \text{ Education}_{\text{jk}} = S_j - S_k$.

$$\Delta \text{ Hours}_{\text{jk}} = (\beta * \rho)_F * \Delta \text{ Education}_{\text{jk}} + \varepsilon_{\text{jk}} \text{ and}$$

$$\Delta \text{ Ln wages}_{\text{jk}} = \rho_F * \Delta \text{ Education}_{\text{jk}} + \sigma_{\text{jk}} \rightarrow \beta_F = \left((\beta * \rho)_F / \rho_F\right)$$

Because education is measured with error, ρ_F and $(\beta * \rho)_{\text{F}}$ are both biased towards 0 (Griliches 1977). However, this bias is easy to correct. Measurement error biases ρ_F and $(\beta * \rho)_{\text{F}}$ towards 0 by the exact same fraction. The ratio of the two is an unbiased estimated of β_{F}, within family labor supply elasticity. Based on the model in section 2, I predict that β_{F} is much larger than 0. In other words, high wage men work much harder than their low wage brothers.

[35] Returns to education are slightly higher in the general population. This is caused by the fact that returns to education in my sample are lower for young men. Returns to education are much closer if I weight the general population to match the age distribution of the brothers sample.

I find that within family labor supply elasticity for the complete sample is large and positive. Empirical results are given in Table 14. A man with one extra year of education earns 4.4% more than his brother and works .6-.7 more hours each week. This is equivalent to a labor supply elasticity of .33-.4. I can easily reject the null hypothesis that $\widehat{\beta}_{F} = \widehat{\beta}_{OLS}$ (from Table 13). The within family labor supply elasticity estimate from Table 13 is .33-.4, very similar to the within family labor supply elasticity estimate of .4 estimated using instrumental variables (Tables 10 and 11). The similarity between $\widehat{\beta}_{F}$ and $\widehat{\beta}_{IV}$ is strong corroboration for my analysis in section 3, which showed that the two regressions estimate the same economic variable.[36]

The model described in section 2 also makes strong predictions about how parents affect labor supply elasticity. Risk sharing between brothers only occurs when adult children support their retired parent. Within family labor supply elasticity is predicted to be high in households with retired parents who are completely dependent on their children's support and low in households where the parent is working or receiving a retirement pension. In other words, β_F is larger than in households with retired parents and smaller in households with working parents.

I find that within family labor supply elasticity is significantly larger in households with retired fathers. In Table 15, I find that within family labor supply elasticity is .25-.32 when the father is working and .37-.46 when the father is not working. The difference between the two elasticities is statistically and economically significant. Empirical results are even stronger when I use fathers' age to instrument for retirement. In Table 16, I find that within family labor supply elasticity is only .16-.25 when the father is under 65 and .44-.50 when the father is over 65. I also find that labor supply elasticity is higher in poor states, where retired men are less likely to receive retirement pensions (because formal sectors jobs are rare). Therefore, retired men in poor states are more dependent on financial support from their adult children. Results are given in Table 17. The results in Tables 15, 16 and 17 are strongly consistent with the model created in this paper.

8. Within Family Elasticity of Consumption with IV

In this section, I study how wage shocks affect three particular consumption goods: food quality, televisions and automobiles. I show that these three goods have different relationships to leisure: food quality is separable from leisure, televisions are complements to leisure and automobiles are substitutes for leisure. In my model, the effects of wage shocks on consumption depend on the interaction between leisure and consumption. Compared to their low wage siblings, men with high wages consume more substitutes for leisure and fewer complements. Therefore, I predict that men who receive exogenous wage shocks consume the same food quality, own fewer televisions and own more cars.

The first measure of consumption studied is food quality. Traditionally, rural Mexicans ate a great deal of corn and beans, and very few animal products such as meat,

[36] If the two methods sample different locations on the distribution β the estimates need not match exactly.

fish, milk or eggs. The food choices were driven by simple economics[37] – animal products are much more expensive than corn and beans. Therefore, I predict that rich men eat substantially more animal products. This prediction is confirmed in table 18 (OLS regression of food quality on wages). A 10% increase in wages increases consumption of meat, milk, wheat bread, and eggs by approximately .2 meals per week. However, recent research by Hurst and Aguiar (2004) shows that quality of food consumed does not change with retirement (when leisure increases dramatically), suggesting that leisure and food quality are separable.[38] Accordingly, I predict that exogenous wage shocks have no effect on food consumption for men from families with risk sharing.

I find that exogenously raising a man's wages by 10% has no effect on food quality consumed. Regression results are given in Table 19. Point estimates from an IV regression of food quality on wages are close to 0 for all food groups. Standard errors are low enough that I can reject the null hypothesis that OLS=IV for meat, eggs, and total food quality. The IV regression corresponds to a policy experiment that raises wages for one child, but holds average family wages fixed. These results are very strong evidence for risk sharing within the family.

The second measure of consumption studied is television ownership. Televisions are a very time-intensive good which are used almost exclusively for leisure. Therefore, it is likely that televisions are a complement to leisure. The model presented in section 2 predicts that men with high wages consume fewer complements to leisure than their low wage siblings. Accordingly, I predict that men who receive an exogenous wage shock own fewer televisions.

I find that exogenously raising a man's wages by 10% reduces the likelihood he owns a television by 2% in 2000 and 3% in 1970. In 2000, standard errors are low enough that I can reject the null that IV=0. Regression results are given in Table 20. These results are consistent with the increase in labor supply observed in Tables 10 and 11. Men who receive an exogenous wage shock work many more hours, so they have less time available to watch television. Regression results are very different when I run a simple OLS regression of television ownership on wages. Using OLS, I find that raising wages by 10% increases television ownership by 2% in 2000 and 3% in 1970. The difference between OLS and IV is consistent with the model predictions. In section 3, I showed that OLS measures the impact of changing average family wages. Men from families with high average wages work about the same number of hours but have more income. Therefore, they will own more televisions (as well as any other normal good).

The third measure of consumption studied is automobile ownership. Driving is almost always faster than walking or taking a bus. Hence, owning a car has more value to people with a higher opportunity cost for time. In other words, cars are a substitute for leisure.[39] The model presented in section 2 predicts that men with high wages consume

[37] The low consumption of dairy and wheat bread by the poor may also be partially driven by ethnic differences in tastes. Because of historical discrimination, Mexicans with higher percentages of Native American ancestry are more likely to be poor. Native Americans have a traditional cuisine based on corn rather than wheat flour. And many Native Americans are lactose intolerant. Therefore, income may be correlated with taste for milk and wheat bread.

[38] Calories consumed are highly positively correlated with hours worked and effort expended (Foster and Rosenzweig 1994).

[39] This is classifying all non-work time as leisure.

more substitutes for leisure than their low wage siblings. Accordingly, I predict that men who receive an exogenous wage shock own more cars.

I find that exogenously raising a man's wage by 10% increases the likelihood he owns a car by 2%-4% in 2000. Standard errors are low enough that I can reject the null that IV=0. Regression results are given in Table 21. These results are very similar to an OLS regression of automobile ownership on wages. Using OLS, I find that raising wages by 10% increases car ownership by 3.5%. I cannot reject the null hypothesis that OLS and IV are identical. The similar results are consistent with model predictions. Men with a high value of time own a car, regardless of whether they use the time saved to work more or for leisure.

9. How Much Do High Wage Children Send to Parents?

The model described in section 2 makes strong predictions about transfers within the family. When adult children earn high wages, they give substantial amounts of money to support their retired parents. When adult children earn low wages, they give much less money. This prediction is absolutely central to the model. If the transfers predicted do not occur, then there is no risk sharing within the family. In this section, I will use data on transfers to directly test this prediction.

I cannot use OLS to study the impact of adult children's wages on transfers given to parents. Most Mexican adults live apart from their parents, so it is impossible to observe adult children's wages. Even if we could observe children's wages, reverse causality makes an OLS regression misleading. On the one hand, high wage children are predicted to give more money to their parents (holding parental wealth fixed). On the other hand, rich parents are predicted to get less money from their children (holding children's wages fixed). In my sample wages for parents and children are highly correlated. Accordingly, the effect of raising children's wages by 10% and not holding parents wages fixed is theoretically ambiguous.

I avoid the problem of missing data by using age and state of birth to impute wages for children. The 2000 Census asks women how many children they have and how old their youngest child is. I assume that children are spaced an average of two years apart,[40] and that children are always born in their mother's birth state and then calculate age and state of birth for each child. I then impute wages for each adult child by assuming that a child earns the mean wage for their age and state or birth. For example, 30-year-old men born in Mexico State have an average wage of 10.6 pesos per hour and 40-year-old men born in Zacatecas have an average wage of 11.2 pesos per hour. I can then regress transfers received by the parents on their child's imputed wage. In all regressions, I control for child's age and state of birth and use the remaining wage variation to identify results.

Imputing missing wage data creates its own set of problems (Hirsch and Schumacher 2004), and it does not prevent the problems of reverse causality. However, I am able to avoid both problems by using school calendar and temperature during childhood to instrument for imputed wage. By assumption, my instruments are

[40] This typically leads to the oldest children born after a woman is 16, except for very large families. The Mexican census does not ask gender of the children.

uncorrelated with family background – so there is no problem of reverse causality. And my instruments are defined by state-age cells, the same as my imputed wages. Therefore, imputing mean wages in place of actual wages does not bias point estimates or misstate standard errors[41] (Bollinger and Hirsch 2004). Accordingly, IV can be used to observe a policy experiment: what happens when wages for children rise, holding parents wages fixed.

In the Mexican Census, parents are only asked about the total transfers they receive, not which child sent the money.[42] I cannot estimate $(\partial t_j / \partial w_j)$, how much child j sends to the parent when his wages go up 10%. Instead, I will estimate $(\partial \sum_{j=1}^{n} t_j)/(\partial \sum_{j=1}^{n} w_j)$, how much do parents receive when mean wage for their children goes up 10%. I use mean school calendar and mean weather during childhood to instrument for mean wages. In all regressions, I control for state of birth and age of children[43] and identify coefficients using state-age variation in average wages. Differences in average wages across states have no effect on my point estimates.

I find that parents get 225-275 more pesos (about $25) a month if we raise mean wages for their adult children's wages by 10%. Empirical results are given in Tables 22 and 23. How much risk sharing does 225-275 pesos represent? In the Table 1, I show that Mexican men earn an average of 2900 pesos a month and Mexican women earn an average of 900 pesos a month. Therefore, a 10% increase in average wages raises mean earnings by 190 pesos a month (holding labor supply fixed). I can then calculate that a 10% wage increase for children increases parents' consumption by 6%-7% and children's consumption by 7%-8%.[44] These results are consistent with complete risk sharing within a family.

Conclusion

This paper presented a model of labor supply and consumption when retired parents are supported by their adult children. I demonstrated that this family arrangement creates complete risk sharing within a family. The model yields three testable predictions: (1) compared to their low wage siblings, children with high wages send more home money to support their parents; (2) compared to their low wage siblings, children with high wages work more hours; (3) compared to their low wage siblings, children with high wages consume more substitutes for leisure and fewer complements. Predictions (2) and (3) both rely on the fact that wage shocks change not only income but also the price of leisure. Therefore, they do not hold in a model with random non-labor income.

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[41] Assuming that the observed mean wage is equal to the unobservable mean wage for the complete population (including nonworkers)..

[42] My model assumes that all transfers are received from children, and not other family. Relaxing that assumption does not change the interpretation of empirical results.

[43] In the empirical regressions, I focus only on children older than 25. Younger children are assumed to be in school, and dropped from the sample completely. For example, suppose a woman has three children and the youngest is 23. I regress the transfers she receives on average wages for the 25 and 27-year-old only.

[44]The typical family in the sample has five children over 25. Therefore, a 6-7% increase in parents' consumption requires only a 2.4%-3% decrease in children's consumption. I calculate percentages by assuming that parents and children start out with the same initial consumption.

I test my model using instrumental variables and data from the 1970 and 2000 Mexican Census. My instruments are correlated with individual wages but not family background. Therefore, my instruments correspond to a policy experiment that raises wages for one individual while holding wages for the rest of the family fixed.

Consistent with prediction (1), I find that parents' consumption increases by 6%-7% when their adult children receive an exogenous wage increase of 10%. Consistent with prediction (2), I find that men who receive an exogenous wage shock of 10% during childhood work 4% more hours throughout their working careers. Consistent with prediction (3), I find that wages have varying effects on consumption. Men who receive an exogenous wage shock of 10% during childhood are 2%-4% more likely to own a car (which is a substitute for leisure), eat the same quality of food and are 2%-3% less likely to own a television (which is a complement for leisure). As an additional check, I also studied the impact of endogenous wage differences between brothers living at home. I found that a man whose wage was 10% higher than that of his brother worked an average of 3%-4% more hours. Consistent with model predictions, labor supply elasticity is higher in households with a retired father.

References

Aguiar, Mark and Hurst, Erik (2004) "Consumption vs. Expenditure" *NBER* Working Paper 10307.

Altonji, Joseph, Hayashi, Fumio and Kotlikoff, Laurence (1992) "Is the Extended Family Altruistically Linked? Direct Tests Using Micro Data" *American Economic Review* 82, 1177-1198.

Altonji, Joseph, Hayashi, Fumio and Kotlikoff, Laurence (1997) "Parental Altruism and Inter Vivos Transfers: Theory and Evidence" *The Journal of Political Economy* 105, 1121-1166.

Angelucci, Manuela and De Giorgi, Giacomo (2006) "Indirect Effects of an Aid Program: The Case of Progresa and Consumption" *IZA* DP No. 1955.

Ashenfelter, Orley and Krueger, Alan (1994) "Estimates of the Economic Return to Schooling from a New Sample of Twins" *The American Economic Review* 84, 1157-1173

Attanasio, Orazio, Meghir, Costas and Szekely, Miguel (2003) "Using Randomised Experiments and Structural Models For 'Scaling Up': Evidence From the PROGRESA Evaluation" IFS EWP 03/05

Ballester, F., Corella, D., Perez-Hoyos, S., Saez, M., and Hervas, A (1997) "Mortality as a Function of Temperature. A Study in Valencia, Spain, 1991-1993" *International Journal of Epidemiology* 26, 551-561.

Baxter, Marianne and Jermann, Urban (1999) "Household Production and the Excess Sensitivity of Consumption to Current Income" *The American Economic Review* 89, 902-920.

Becker, Gary (1981) "Altruism within the Family and Selfishness in the Marketplace" *Economica* 48, 1-15.

Becker, Gary and Tomes, Nigel (1976) "Child Endowment and the Quantity and Quality of Children" *The Journal of Political Economy* 84, S143-S162.

Becker, Gary, Philipson, Tomas and Soares, Rodrigo (2003) "The Quantity and Quality of Life and the Evolution of World Inequality" *NBER* Working Paper 9765

Behrman, Jere and Rosenzweig, Mark (2002) "Parental Allocations to Children: New Evidence on Bequest Differences Among Siblings" *PIER* Working Paper 02-007.

Bergstrom, Theodore, Blume, Lawrence and Varian, Hal (1986) "The Private Provision of Public Goods" *Journal of Public Economics* 29, pages 25-49.

Bergstrom, Theodore (1989) "A Fresh Look at the Rotten Kid Theorem – and Other Household Mysteries" *The Journal of Political Economy* 97, 1138-1159.

Bollinger, Christopher and Hirsch, Barry (2004) "Match Bias Due to Earnings Imputation: When Does It Matter" Working Paper downloaded

Bound, John, Brown, Charles, Duncan, Greg and Rodgers, Willard (1989) "Measurement Error in Cross-Sectional and Longitudinal Labor Market Surveys: Results from Two Validation Studies" *NBER* Working Paper 2884

Browning, Martin, Hansen, Lars Peter and Heckman, James (1999) "Micro Gata and General Equilibrium Models" *Handbook of Macroeconomics* Volume 1, 543-633

Camerer, Colin, Babcock, Linda and Loewenstein, George (1997) "Labor Supply of New York City Cabdrivers: One Day at a Time" *The Quarterly Journal of Economics* 112, 407-441.

Cancian, Frank (1965) *Economics and Prestige in a Maya Community* (Stanford University Press).

Cancian, Frank; (1992) *The Decline of Community in Zinacantan* (Stanford University Press).

Cancian, Frank (1972) *Change and Uncertainty in a Peasant Economy, the Maya Corn Farmers of Zinacantan* (Stanford University Press).

Card, David (1995) "Using Geographic Variation in College Proximity to Estimate the Return to Schooling" in *Aspects of Labor Market Behavior: Essays in Honor of John Vanderkamp* (University of Toronto Press).

Card, David (2001) "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems" *Econometrica* 69, 1127-1160

Carneiro, Pedro and Heckman, James (2002) "The Evidence on Credit Constraints in Post-Secondary Schooling" *NBER* working Paper 9055.

Chiquiar, Daniel and Hanson and Gordon (2002) "International Migration, Self-Selection, And the Distribution of Wages: Evidence From Mexico and the United States" *NBER* Working Paper 9242.

Conley, Dalton and Glauber, Rebecca (2005) "Sibling Similarity and Differences in Socioeconomic Status: Life Course and Family Resource Effects" *NBER* Working Paper1320.

Cremer, H. and Pestieau, P. (1998) "Delaying Inter Vivos Transmissions under Asymmetric Information" *Southern Economic Journal* 65, pages 322-330.

Domeij, David and Floden, Martin (2006) "The Labor-Supply Elasticity and Borrowing Constraints: Why Estimates are Biased" *Review of Economic Dynamics* 9, 242-262.
Duflo, Esther and Udry, Christopher (2004) "Intrahousehold Resource Allocation in Cote d'Ivoire: Social Norms, Separate Accounts and Consumption Choices" *NBER* Working Paper 10498.
Dustmann, Christain and Micklewright, John (2001) "Intra-Household Transfers and the Part-Time Work of Children" Working Paper.
Farber, Henry (2003) "Is Tomorrow Another Day? The Labor Supply of New York Cab Drivers" *NBER* working paper 9706.
Fehr, Ernst and Gotte, Lorenz (2004) "Do Workers Work More if Wages are High? Evidence from a Randomized Field Experiment" *IZA* DP 1002.
Fischel, William (2003) "'Will I See You In September' An Economics Explanation for the Summer School Vacation" Working Paper.
Foster, Andrew and Rosenzweig, Mark (1994) "A Test for Moral Hazard in the Labor Market: Contractual Arrangements, Effort and Health" *A Review of Economics and Statistics* 76, 213-227.
Gatti, Roberta (2005) "Family Altruism and Incentives" *Scandinavian Journal of Economics* 107, 67-81.
Gertler, Paul and Gruber, Jonathan (2002) "Insuring Consumption Against Illness" *The American Economic Review* 92, 51-70.
Grandolini, Gloria and Cerda, Luis (1998) "The 1997 Pension Reform In Mexico: Genesis and Design Features" Working paper .
Griliches, Zvi (1997) "Estimating the Returns to Schooling: Some Econometric Problems" *Econometrica* 45; 1-22.
Griliches, Zvi (1979) "Siblings Models and Data in Economic: Beginnings of a Survey" *The Journal of Political Economy* 87, S37-S64.
Hamilton, W.D. (1963) "The Evolution of Altruistic Behavior" *American Naturalist* 97, pages 354-356.
Harmon, Colm and Walker, Ian (1995) "Estimating the Economic Return to Schooling for the United Kingdom" *American Economic Review* 85, 1278-1286.
Hayashi, Fumio (1982) "The Permanent Income Hypothesis: Estimation and Testing by Instrumental Variables" *The Journal of Political Economy* 90, 895-916.
Hayashi, Fumio; Altonji, Joseph; Kotlikoff; Lawrence (1996) "Risk sharing Between and Within Families" *Econometrica* 64, 261-294.
Heckman, James, Urzua, Sergio and Vytlacil, Edward (2006) "Understanding Instrumental Variables In Models with Essential Heterogeneity" *The Review of Economics and Statistics* 88, 389-432.
Heckman, James, Lalonde, Robert and Jeffrey Smith (1999) "The Economics and Econometrics of Active Labor Market Programs" *Handbook of Labor Economics* Volume 3, Edited by A. Ashenfelter and D. Card.
Hirsch, Barry and Schumacher, Edward (2004) "Match Bias in Wage Gap Estimates Due to Earnings Imputation" *Journal of Labor Economics* 22, 689-722
Imbens, Guido, Rubin, Donald and Sacerdote, Bruce (2001) "Estimating the Effect of Unearned Income on Labor Earnings, Savings and Consumption: Evidence from a Survey of Lottery Players" *The American Economic Review* 91, 778-794.
Jayachandran, Seema (2006) "Selling Labor Low: Responses to Productivity Shocks in Developing Countries" *Journal of Political Economy* 114, 538-575.
Juster, F. Thomas and Stafford, Frank (1991) "The Allocation of Time: Empirical Findings, Behavioral Models, and Problems of Measurement" *Journal of Economic Literature* 29, 471-522.
Lang, Gunter (2001) "Global Warming and German Agriculture: Impact Estimations Using a Restricted Profit Function" *Environmental and Resource Economics* 29, 97-112.
Lechene, Valerie and Preston, Ian (2005) "Household Nash Equilibrium with Voluntarily Contributed Public Goods" *IFS* Working Paper 2005.
Lindsay, Cotton (1973) "Real Returns to Medical Education" *The Journal of Human Resources* 8, 331-348.
Mace, Barbara (1991) "Full Insurance in the Presence of Aggregate Uncertainty" *The Journal of Political Economy* 99, 928-956.
Mincer, Jacob (1958) "Investment in Human Capital and Personal Income Distribution" *The Journal of Political Economy* 66, 281-302.
Mulligan, Casey and Rubinstein, Yonah (2005) "Selection, Investment and Women's Relative Wages since 1975" *NBER* working paper 11159.
Mundlak, Yair (1978) "On the Pooling of Time Series and Cross Section Data" *Econometrica* 46, 69-85

Nugen, Jeffrey and Gillaspy, R. Thomas (1983) "Old Age Pensions and Fertility in Rural Areas of Less Developed Countries: Some Evidence from Mexico" *Economic Development and Cultural Change* 31, 809-829.
Oettinger, Gerald (1999) "An Empirical Analysis of the Daily Labor Supply of Stadium Vendors" *The Journal of Polical Economy* 107, 360-392.
Pahlavanian, Ali and Silk, Wendy (1988) "Effect of Temperature on Spatial and Temporal Aspects of Growth in the Primary Maize Root" *Plant Physiology* 87, 529-532.
Pastenes, Claudio and Horton, Peter (1996) "Effect of High Temperature on Photosynthesis in Beans" *Plant Physiology* 112, 1253-1260.
Paulson, Anna (2000) "Insurance Motives for Migration: Evidence from Thailand" Working Paper.
Peterson, Thomas C. and Russell S. Vose (1997) "An overview of the Global Historical Climatology Network temperature data base" *Bulletin of the American Meteorological Society* 78, 2837-2849.
Pischke, Jorn-Steffen (2003) "The Impact of Length of the School Year on Student Performance and Earnings: Evidence from the German Short School Year" NBER Working Paper 9964.
Rhoda, Richard (1983) "Rural Development and Urban Migration: Can We Keep Them Down on The Farm?" *International Migration Review* 17, 34-64.
Rosenzweig, Mark and Stark, Oded (1989) "Consumption Smoothing, Migration and Marriage: Evidence from Rural India" *The Journal of Political Economy* 97, 905-926.
Ruggles, Steven; Sobek, Matthew; Alexander, Trent; Fitch, Catherine A; Goeken, Ronald; Hall, Patricia Kelly; King, Miriam and Ronnander, Chad (2004). "Integrated Public Use Microdata Series: Version 3.0 [Machine-readable database]" (Minneapolis, MN: Minnesota Population Center [producer and distributor]) 1960, 1970, 1990 and 2000 Mexican census data http://www.ipums.org.
Schoeck, Helmut; Envy (1969) *A Theory of Social Behavior* translated by Martin Secker & Warburg Limited;Harcourt, Brace & World, New York).
Soloveichik, Rachel (2006) "In Sickness and In Health, Divorce Law and Risk sharing within Marriage" Working Paper.
Spence, Michael (1973) "Job Market Signaling" *Quarterly Journal of Economics* 87, 355-374.
Staiger, Douglas and Stock, James (1997) "Instrumental Variables Regression with Weak Instruments" *Econometrica* 65, 557-586.
Stevenson, David and Baker, David (1987) "The Family-School Relation and the Child's School Performance" *Child Development* 58, 1348-1357.
Townsend, Robert (1995) "Consumption Insurance: An Evaluation of Risk-Bearing Systems in Low Income Economies" *Journal of Economic Perspectives* 9, 83-102.
Townsend, Robert (1994) "Risk and Insurance in Village India" *Econometrica* 62, 539-591.
Trudgill, D.L., Honek, A., Li, D. and Van Straalen, N.M (2005) "Thermal time – concepts and utilities" *Annals of Applied Biology* 146, 1-14.
Varian, Hal (1994) "Sequential Contributions to Public Goods" *Journal of Public Economics* 53, 165-186
Warr, P (1983) "The Private Provision of a Public Good is Independent of the Distribution of Income" *Economic Letters* 13, 207-211.

Table 1: Summary Statistics for the 2000 Mexican Census

	Adults 25-45	Adults 45-64	Adults 65+
Average Age	33.55	53.13	73.65
% Female	52.7%	51.9%	53.4%
% In School	3.3%	1.0%	0.5%
Mean Years Education	8.00008	5.1652	3.0232
% Men Married	80.17%	87.35%	73.63%
% Women Married	77.34%	70.16%	38.76%
% Men Working	90.59%	81.17%	42.30%
% Women Working	39.25%	28.16%	10.18%
Men's Earnings Last Month	3,075.00 Ps.	2,555.24 Ps	649.55 Ps
Men's Non-Labor Income Last Month	43.92 Ps.	235.01 Ps	564.58 Ps
Men's Transfers from Family	14.79 Ps.	54.54 Ps	118.33 Ps
Women's Earnings Last Month	1,020.06 Ps.	610.94 Ps.	101.83 Ps.
Women's Non-Labor Income Last Month	42.44 Ps.	158.18 Ps.	270.41 Ps.
Women's Transfers from Family	63.24 Ps.	108.85 Ps.	154.53 Ps.
% Disabled	2.2%	5.1%	18.3%
Number People	2,366,939	1,171,313	511,169

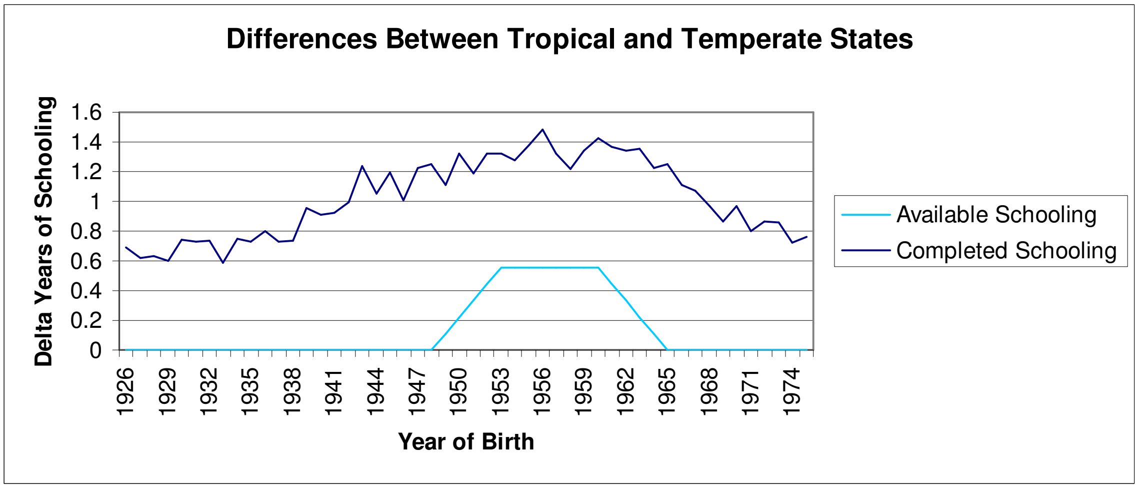
These statistics are for all adults in the Mexican Census not born in Mexico City. Observations are weighted by the sample weight given in the Census. Individual with invalid data for one question are removed for that summary statistic, but used for other observations. The official exchange rate in February 2000 was approximately 9.4 Pesos to one American dollar.

Table 2: Summary Statistics for the 1970 Mexican Census

	Adults 25-45	Adults 45-64	Adults 65+
Average Age	33.30	52.83	72.24
% Female	51.7%	50.9%	51.6%
% In School	2.7%	1.2%	1.1%
Mean Years Education	2.32	1.79	1.24
% Men Married	82.50%	87.89%	76.0%
% Women Married	82.2%	71.06%	44.0%
% Men Working	92.7%	91.1%	71.8%
% Women Working	15.0%	14.9%	10.9%
Men's Income Last Month	945.86 Ps.	1003.40 Ps.	540.87 Ps.
Women’s Income Last Month	131.81 Ps.	126.72 Ps.	72.98 Ps.
Number People	94,716	44,987	16,794

These statistics are for all adults in the Mexican Census not born in Mexico City. Individual with invalid data for one question are removed for that summary statistic, but used for other observations. In 1970, the Mexican pesos was fixed at 12.5 pesos for 1 American dollar.

Figure 1: Comparison of Men born in Temperate and Tropical States



This figure demonstrates that the shorter school calendar significantly reduces completed educated in temperate states. The top line is:
Δ Education = (Mean Education Tropical States) – (Mean Education Temperate States)
The second line is:
Δ Years of School = (Years of School Tropical States) – (Years of School Temperate States)

Table 3: First Stage Regression of Education on Months School Missed for Men 25-74 in 2000 Census

$$\text{Education}_j = b*X_j + d*(\text{Months of School Missed 6-17})_j + e_j$$

	Dependent variable: Years Education		
Months of School Missed ages 6-17 (d)	-0.090	-0.085	-0.073
	(0.008)	(0.007)	(0.007)
Control for Birth State & Age?	Y	Y	Y
Control for Birth State Trends?	N	Y	Y
Restrict Sample to Men with Valid Wages?	N	N	Y

Observations are weighted by the sampling weight given in the census, and standard errors are clustered by cohort. Men with invalid data are excluded.

This table provides additional evidence the short school year hurt men in temperate states. Depending on the specification, one month less of school reduces completed education by .07 to .09 years.

Table 4: Regression of Wages on Years Education for Men 25-74 in 2000 Census

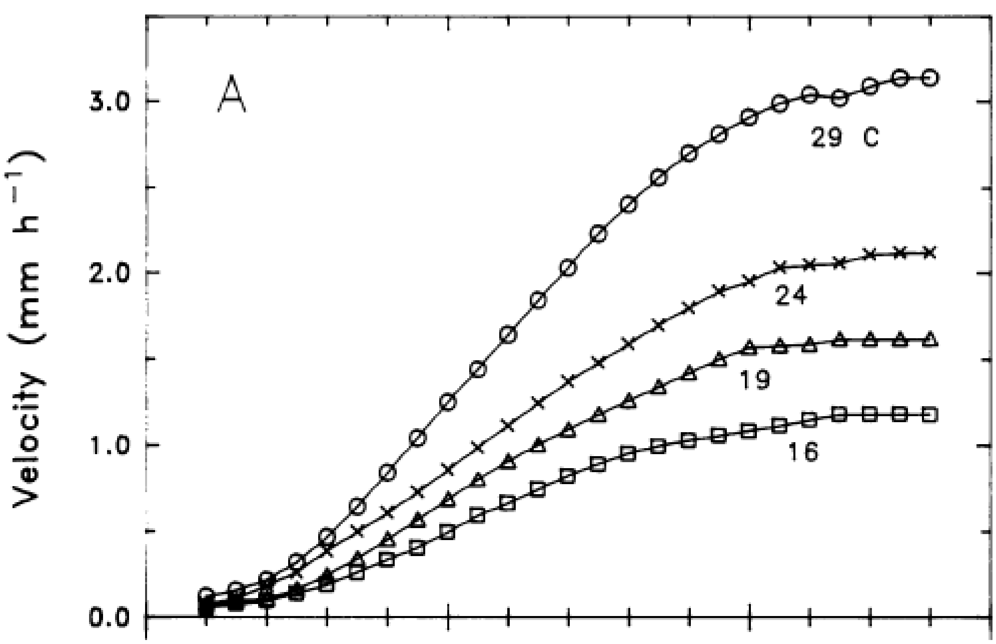
$$\text{Ln(wages)}_j = f{*}X_j + \rho{*}\text{Education}_j + \sigma_j$$

	Calendar IV		
Return to Education (ρ)	9.67%	10.11%	9.94%
	(1.00%)	(.99%)	(1.13%)
	OLS		
Return to Education (ρ)	9.32%	9.27%	9.27%
	(.05%)	(.05%)	(.05%)
Control for Birth State & Age?	Y	Y	Y
Control for State of Residence?	N	Y	Y
Control for Birth State Trends?	N	N	Y

Controls used are identical to Table 3. Men with invalid data are excluded from the sample.

This table compares OLS and IV regression of wages on education. Both estimates find returns to education of about 10%. In other words, one year of education increases wages by 10%.

Figure 2: Growth Rate for Corn As a Function of Temperature



This figure shows that corn grows substantially faster in warm temperature.

Table 5: Regression of School Attendance on Temperature Last Month for Boys 6-17

$$\%Enrollment_j = b*X_j + d*(\text{Mean Temperature Last Month})_j + e_j$$

	Dependent Variable: %In School Now	
Mean Temperature Last Month (d)	-1.31%	-.74%
	(.49%)	(.39%)
Control for State Fixed Effects?	Y	Y
Control for State Trends?	N	Y

In all specifications, I control for age and year by including a dummy for each age-year cell. Observations are weighted by the sampling weight given in the census, and standard errors are clustered by state-year cell.

Table 6: First Stage Regression of Education on ΔTemp 6-17 for Men in 1970 Census

$$Education_j = b*X_j + d*(\Delta \text{ Temp ages 6-17})_j + e_j$$

	Dependent variable: Years Education		
ΔTemp ages 6-17 (d)	-.471	-.096	-.194
	(.102)	(.104)	(.112)
Control for Birth State & Age?	Y	Y	Y
Control for Birth State Trends?	N	Y	Y
Restrict Sample to Men with Valid Wages?	N	N	Y

Controls identical to Table 3

Table 7: First Stage Regression of Education on ΔTemp 6-17 for Men in 2000 Census

$$Education_j = b*X_j + d*(\Delta \text{ Temp ages 6-17})_j + e_j$$

	Dependent variable: Years Education		
ΔTemp ages 6-17 (d)	-.445	-.444	-.357
	(.065)	(.055)	(.058)
Control for Birth State & Age?	Y	Y	Y
Control for Birth State Trends?	N	Y	Y
Restrict Sample to Men with Valid Wages?	N	N	Y

Controls identical to Table 3

Tables 5, 6 and 7 demonstrate that high temperatures during childhood result in a short-term decrease in school attendance, and a long-term reduction in completed education. Therefore, random temperature variation can be used as an instrument for education.

Table 8: Regression of Log Wages (Imputed) on Education for Men 25-74 in 1970

$$\text{Ln(imputed wages)}_j = f^*X_j + \rho^*\text{Education}_j + \sigma_j$$

		Weather IV	
Return to Education (ρ)	13.66%	15.34%	19.20%
	(3.66%)	(3.26%)	(11.20%)
		OLS	
Return to Education (ρ)	11.87%	10.52%	10.50%
	(.09%)	(.09%)	(.09%)
Control for Birth State & Age?	Y	Y	Y
Control for Current State of Residence?	N	Y	Y
Control for Birth State Trends?	N	N	Y

Controls used are identical to Table 3. The Census does not give earned income, but only total monthly income. If men include transfers given or received in their income, a regression of monthly income on education shocks are biased downwards from risk sharing within the family. I avoided that problem by using occupation to predict income.

Table 9: Regression of Wages on Years Education for Men 25-74 in 2000 Census

$$\text{Ln(imputed wages)}_j = f^*X_j + \rho^*\text{Education}_j + \sigma_j$$

		Temperature IV	
Return to Education (ρ)	10.61%	9.71%	10.82%
	(1.77%)	(1.77%)	(1.99%)
		OLS	
Return to Education (ρ)	9.32%	9.27%	9.27%
	(.05%)	(.05%)	(.05%)
Control for Birth State & Age?	Y	Y	Y
Control for State of Residence?	N	Y	Y
Control for Birth State Trends?	N	N	Y

Controls used are identical to Table 3. Men with invalid data are excluded from the sample.

Tables 8 and 9 compare OLS and IV regression of wages on education. I find that OLS and IV are quite close – suggesting that IV is not serious biased.

Table 10: Regression of Labor Supply on Imputed Wages in 2000

$$\text{Hours Worked}_j = g^*X_j + \gamma^* w_f + \beta^*(w_j - w_f) + \varepsilon_j$$

Dependent Variables: Hours Worked and Wages Earned			
		Weather IV	
10% Wage Increase (β)	1.54	1.39	1.87
	(.58)	(.58)	(.48)
		Calendar IV	
10% Wage Increase (β)	1.42	1.39	1.48
	(.30)	(.29)	(.28)
		OLS estimate	
10% Wage Increase (γ)	.27	.25	.25
	(.01)	(.01)	(.01)
Control for Birth State & Age?	Y	Y	Y
Control for Current State of Residence	N	Y	Y
Control for Birth State Trends?	N	N	Y

Controls identical to Table 3. The results presented are **not** a regression of labor supply on actual wages. Instead, I regress labor supply on wages imputed from education.

Table 11: Regression of Labor Supply on Imputed Wages in 1970

$$\text{Months Worked}_j = g^*X_j + \gamma^* w_f + \beta^*(w_j - w_f) + \varepsilon_j$$

Dependent Variable: Mean Months Worked Last Year			
		Weather IV	
10% Wage Increase (β)	.386	0.363	-.641
	(.150)	(.134)	(.851)
		OLS estimate	
10% Wage Increase (γ)	.077	.071	.070
	(.003)	(.003)	(.003)
Control for Birth State & Age?	Y	Y	Y
Control for Current State of Residence	N	Y	Y
Control for Birth State Trends?	N	N	Y

Controls and procedure identical to Table 10.

In Tables 10 and 11, I use instrumental variables to create a policy experiment: wages for one child increase, but wages for the rest of the family are held fixed. In that policy experiment, I find that raising wages by 10% increases labor supply by 4%.

In contrast, OLS measures the effect of raising children's wages, but not holding family wages fixed. Because wages for children and parents are highly correlated, OLS is closest to an experiment that raises wages for everybody in a family together. In that policy experiment, I find that raising wages by 10% increases labor supply by only .7%.

Table 12: Summary Statistics for the Brothers Sample

	Sample of Brothers			Complete Sample		
	Men 25-45	Men 45-64	Men 65-74	Men 25-45	Men 45-64	Men 65-74
Average Age	30.55	50	67.06	33.54	53.03	68.87
Mean Years Education	8.63	5.47	3.37	8.75	6.17	3.86
%Married	19.14%	13.61%	15.11%	80.17%	87.35%	73.63%
%Working	81.47%	73.97%	49.68%	90.59%	81.17%	42.30%
Earnings Last Month	1958 Ps.	1385 Ps.	256 Ps.	3,075 Ps.	2,555 Ps	650 Ps
Non-Labor Income Last Month	13.71 Ps.	67.68 Ps.	108.87 Ps.	43.92 Ps.	235.01 Ps	564.58 Ps
Transfers from Family	6.57 Ps.	11.83 Ps.	71.61 Ps.	14.79 Ps.	54.54 Ps	118.33 Ps
% Disabled	5.0%	11.6%	12.9%	2.2%	5.1%	18.3%
Number People	53,651	4,012	79	2,366,939	1,171,313	511,169

These statistics are for all pairs of brothers 25-74 who are currently living in their parents house. I exclude families where one either brother has invalid education or was born in Mexico City. Observations are weighted by the sample weight given in the Census. Individual with invalid data for one question are removed for that summary statistic but used for other observations. The official exchange rate in February 2000 was approximately 9.4 Pesos to one American dollar.

Table 12 compares summary statistics for the sample of brothers living at home with summary statistics for the general population. I find that men living at home are much younger and much less likely to be married. They are also slightly less likely to be working and slightly more likely to be disabled.

Table 13: OLS Regression of Labor Supply and Wages on Education

$$\text{Wages}_j = f*X_j + \rho*\text{Education}_j + \sigma_j$$

$$\text{Hours Worked}_j = g*X_j + (\gamma*\rho)*\text{Education}_f + (\beta*\rho)*(\text{Education}_j - \text{Education}_f) + \varepsilon_j$$

	Dependent Variable: Hours Worked					
	Brothers Sample			Complete Population		
Labor Supply Response (γ*ρ)	.257	.217	.216	.510	.262	.287
	(.031)	(.031)	(.032)	(.011)	(.010)	(.011)
	Dependent Variable: Wages Earned					
	Brothers Sample			Complete Population		
Return to Education (ρ)	7.34%	7.42%	7.22%	9.29%	9.75%	9.32%
	(.12%)	(.12%)	(.12%)	(.03%)	(.03%)	(.02%)
Implied Labor Supply Elasticity (γ)	0.088	0.073	0.075	0.137	0.067	0.077
Control for Control for Ages?	N	Y	Y	N	Y	Y
Control for State of Birth?	N	N	Y	N	N	Y

In all regressions, I restrict the sample to men 25-74 who report valid data. Observations are weighted by the sample weights given. In the second column, I control for age by including a dummy for each year of age. In the third column, I control for state of birth by including a dummy for each state of birth.

Table 13 compares OLS labor supply elasticity for brothers living at home with OLS labor supply elasticity for the general population. I find that the two are reasonably similar, suggesting that the highly selected sample of brothers living at home (and hence observable) can be used as a proxy for the complete sample of brothers (who are unobservable). In Mexico, returns to education increase with age – so the slightly lower returns to education for the brothers sample is unremarkable.

Table 14: Within family Regression of Labor Supply and Wages on Education

$$\Delta Wages_{jk} = f^*(X_j - X_k) + \rho^* \Delta Education_{jk} + \sigma_{jk}$$

$$\Delta Hours\ Worked_{jk} = f^*(X_j - X_k) + (\beta^*\rho)^*\Delta Education_{jk} + \varepsilon_{jk}$$

	Dependent Variable: ΔHours Worked Last Week		
Labor Supply Response ($\beta^*\rho$)	.619	.590	.711
	(.043)	(.044)	(.048)
	Dependent Variable: ΔWages Earned		
Returns to Education (ρ)	4.47%	4.47%	4.42%
	(.17%)	(.17%)	(.18%)
Implied Labor Supply Elasticity (β)	0.346	0.330	0.402
Control for Control for Ages?	N	Y	Y
Control for Control for Average Education	N	N	Y

ΔEducation = Years Education Older Brother – Years Education Younger Brother
ΔHours = Hours Worked Older Brother – Hours Worked Younger Brother,
ΔWage = Log Hourly Wage Older Brother – Log Hourly Wage Younger Brother.
Families are only included in the labor supply regression of both brothers report valid hours, and only included in the wage regression if both brothers report valid wages.

I control for ages by including a dummy for each year of age for brother 1 and brother 2, and control for education by including a dummy for each year of brother 1's schooling, from 0 to 20. For simplicity, I compute labor supply elasticity using 40 hour week mean labor supply, rather than the actual mean which is slightly lower.

In Table 14, I compare labor supply and wages for brothers with different education. Comparing two brothers, I find that the brother with 1 more year of education earns 4.5% more, and works .6-.7 hours more per week. The low point estimates for return to education are caused by measurement error biasing results towards 0 (Griliches 1977). However, my estimates for labor supply elasticity are unbiased because the two biases cancel out when I divide.

Table 15: Within family Labor Supply Elasticity, Split By Father's Work Status

$$\Delta \text{Wages}_{jk} = f^*(X_j - X_k) + \rho^* \Delta \text{Education}_{jk} + \sigma_{jk}$$

$$\Delta \text{Hours Worked}_{jk} = f^*(X_j - X_k) + (\beta^*\rho)^* \Delta \text{Education}_{jk} + \varepsilon_{jk}$$

	Dependent Variable: ΔHours Worked Last Week					
	Father Working			Father Retired		
Labor Supply Response (β*ρ)	.478	.467	.594	.729	.695	.861
	(.063)	(.064)	(.069)	(.087)	(.089)	(.098)
	Dependent Variable: ΔWages Earned					
	Father Working			Father Retired		
Returns to Education (ρ)	4.54%	4.48%	4.51%	4.83%	4.88%	4.71%
	(.26%)	(.26%)	(.28%)	(.34%)	(.35%)	(.38%)
Implied Labor Supply Elasticity (β)	0.263	0.261	0.329	0.377	0.356	0.457
Control for Control for Ages?	N	Y	Y	N	Y	Y
Control for Control for Average Education	N	N	Y	N	N	Y

Controls and technique are identical to Table 14. Families without a father present are excluded.

Table 16: Within family Labor Supply Elasticity, Split By Father's Age

	Dependent Variable: ΔHours Worked Last Week					
	Father<65			Father 65+		
Labor Supply Response (β*ρ)	.308	.303	.481	.775	.753	.838
	(.071)	(.072)	(.078)	(.054)	(.055)	(.061)
	Dependent Variable: ΔWages Earned					
	Father <65			Father 65+		
Returns to Education (ρ)	4.89%	4.82%	4.86%	4.23%	4.28%	4.18%
	(.27%)	(.28%)	(.30%)	(.21%)	(.21%)	(.23%)
Implied Labor Supply Elasticity (β)	0.157	0.157	0.247	0.458	0.440	0.501
Control for Control for Ages?	N	Y	Y	N	Y	Y
Control for Control for Average Education	N	N	Y	N	N	Y

Controls and technique are identical to Table 14. Families without a father present are excluded.

In Tables 15, I demonstrate that labor supply elasticity is larger when the father is retired. In Table 16, I find similar results when I use father's age to instrument for retirement. These results are consistent with my model. In my model, risk sharing only occurs when adult children support their retired parent. Therefore, labor supply elasticity is larger in families with a retired parent.

Table 17: Within family Labor Supply Elasticity, Split by Mean State Education

$$\Delta \text{Wages}_{jk} = f^*(X_j - X_k) + \rho^* \, \Delta \text{Education}_{jk} + \sigma_{jk}$$

$$\Delta \text{Hours Worked}_{jk} = f^*(X_j - X_k) + (\beta^*\rho)^* \Delta \text{Education}_{jk} + \varepsilon_{jk}$$

	Dependent Variable: ΔHours Worked Last Week					
	Low Education States			High Education States		
Labor Supply Response (β*ρ)	.671	.616	.711	.560	.542	.697
	(.057)	(.058)	(.063)	(.066)	(.066)	(.073)
	Dependent Variable: ΔWages Earned					
	Low Education States			High Education States		
Returns to Education (ρ)	3.67%	3.66%	3.66%	5.29%	5.32%	5.20%
	(.23%)	(.23%)	(.25%)	(.24%)	(.25%)	(.27%)
Implied Labor Supply Elasticity (β)	0.457	0.421	0.486	0.265	0.255	0.335
Control for Control for Ages?	N	Y	Y	N	Y	Y
Control for Control for Average Education	N	N	Y	N	N	Y

Controls and technique are identical to Table 14.

In Table 17, I compare labor supply elasticity in high education states (mean education more than 8.5 years) and low education states (mean less than 8.5 years). I find that labor supply elasticity is much larger in low education states. This is consistent with a higher rate of pension coverage in rich states – parents receiving a retirement pension don't need support from their children. The larger returns to education in rich states are caused by non-linearities in the return to school: OLS finds a return to primary school of only 6% - but a 15% return to college.

Table 18: OLS Regression of Food Consumption on Imputed Wages

$$\text{Food Consumption}_j = h^*X_j + \delta^* w_f + \tau^*(w_j - w_f) + \varepsilon_j$$

	Dependent Variable: Days Ate Meat Last Week		
10% Wage Increase (δ)	.217	.197	.194
	(.002)	(.003)	(.002)
	Dependent Variable: Days Ate Fish Last Week		
10% Wage Increase (δ)	.028	.027	.027
	(.001)	(.001)	(.001)
	Dependent Variable: Days Ate Wheat Bread Last Week		
10% Wage Increase (δ)	.189	.159	.159
	(.003)	(.003)	(.003)
	Dependent Variable: Days Ate Eggs Last Week		
10% Wage Increase (δ)	.196	.176	.173
	(.003)	(.003)	(.003)
	Dependent Variable: Days Ate Dairy Last Week		
10% Wage Increase (δ)	.245	.214	.213
	(.003)	(.003)	(.003)
	Dependent Variable: Food Quality Index		
10% Wage Increase (δ)	.068	.060	.059
	(.001)	(.001)	(.001)
Controls for Birth State & Age?	Y	Y	Y
Control for Current State of Residence	N	Y	Y
Controls for Household Composition	N	N	Y

In all specifications, I restrict the sample to men 25-74 with valid education and state of birth. I control for age by including a dummy for each year of age, and control for state of birth by including a dummy for each state. Observations are weighted by the sampling weight given in the census, and standard errors are clustered by cohort.

In the last row, I used the complete information on food consumption to create a food quality index. I created the index by regressing ln(monthly income) on 8 dummy variables for eating meat 0-7 days, 8 dummy variables for eating fish 0-7, etc. In other words, my food quality index is equivalent to monthly income predicted from food consumption.

Table 18 measures the effect of raising wages for one individual, but not holding family wages fixed. Because wages for children and parents are highly correlated, OLS is closest to an experiment that raises wages for everybody in a family together. In that policy experiment, I find that raising wages by 10% increases the quality of food consumption dramatically. This is consistent with common sense: poor people cannot afford to eat meat and eggs every day.

Table 19: IV Regression of Food Consumption on Imputed Wages

$$\text{Food Consumption}_j = h^*X_j + \delta^* w_f + \tau^*(w_j - w_f) + \varepsilon_j$$

	Dependent Variable: Days Ate Meat Last Week		
10% Wage Increase (τ)	-.065	-.013	-.001
	(.102)	(.083)	(.081)
	Dependent Variable: Days Ate Fish Last Week		
10% Wage Increase (τ)	.019	.022	.025
	(.047)	(.043)	(0.043)
	Dependent Variable: Days Ate Bread Last Week		
10% Wage Increase (τ)	.016	.085	.112
	(.121)	(.099)	(.097)
	Dependent Variable: Days Ate Eggs Last Week		
10% Wage Increase (τ)	-.050	.000	.009
	(.110)	(.089)	(0.088)
	Dependent Variable: Days Ate Dairy Last Week		
10% Wage Increase (τ)	-.034	.043	.053
	(.137)	(.109)	(.109)
	Dependent Variable: Food Quality Index		
10% Wage Increase (τ)	-.014	.005	.009
	(.030)	(.023)	(.022)
Controls for Birth State & Age?	Y	Y	Y
Control for Current State of Residence?	N	Y	Y
Control for Household Composition?	N	N	Y

Controls identical to Table 18.

Table 19 measures the effect of raising wages for one individual, while holding wages for the rest of the family fixed. I find that individual wages have almost no effect on quality of food consumed. This suggests that high wage men are sending their extra earnings to parents and siblings and keeping very little for themselves. These results are consistent with complete risk sharing in the family.

Table 20: Regression of Television Ownership on Imputed Wages

$$(\%\text{Own television})_j = h*X_j + \delta*w_f + \tau*(w_j - w_f) + \varepsilon_j$$

Dependent Variable: % Population that Lives in Household With A Television in 2000				
	IV Estimate, With Temperature As An Instrument			
10% Wage Increase (τ)	-2.1%	-1.7%	-2.7%	-2.7%
	(.8%)	(.8%)	(.9%)	(.9%)
	IV Estimate, With School Calendar As An Instrument			
10% Wage Increase (τ)	-1.9%	-1.5%	-2.4%	-2.0%
	(.6%)	(.5%)	(.6%)	(.6%)
	OLS Estimate			
10% Wage Increase (δ)	1.9%	1.8%	1.8%	1.9%
	(.0%)	(.0%)	(.0%)	(.0%)
Dependent Variable: % Population that Lives in Household With A Television in 1970				
	IV Estimate, With Temperature As An Instrument			
10% Wage Increase (τ)	-2.7%	-1.7%	-2.1%	-14.7%
	(2.1%)	(1.7%)	(2.0%)	(22.2%)
	OLS Estimate			
10% Wage Increase (δ)	3.3%	2.8%	3.3%	3.3%
	(.0%)	(.0%)	(.0%)	(.0%)
Control for Birth State & Age?	Y	Y	Y	Y
Control for Current State of Residence	N	Y	N	N
Control for Household Composition	N	N	Y	N
Control for Birth State Trends?	N	N	N	Y

Controls are identical to Table 18 except for the last column. In the last column, I include separate trends for each birth state.

In Tables 20, I use instrumental variables to create a policy experiment: raise wages for one child while holding wages for the rest of the family fixed. I find that increasing wages by 10% decreases television ownership by 2%-3% in 1970 and 2000. This is consistent with the increase in labor supply observed in Tables 10 and 11 – men working long hours do not have time to watch television and are less like to own televisions.

In contrast to the IV policy experiment, OLS measures the effect of a policy experiment that raises wages for the complete family. I find that increasing average family wages by 10% increases television ownership by 3% in 1970 and 2% in 2000. This is consistent with standard demand theory – televisions are a normal good. When labor supply is held nearly constant (like we observe in Tables 10 and 11), rich men are more likely to own televisions.

Table 21: Regression of Automobile Ownership on Imputed Wages

$$(\%\text{Own car})_j = h^*X_j + \delta^* w_f + \tau^*(w_j - w_f) + \varepsilon_j$$

Dependent Variable: % Population that Lives in Household With A Car				
	IV Estimate, With Temperature As An Instrument			
10% Wage Increase (τ)	3.73%	3.93%	3.58%	4.46%
	(.92%)	(.94%)	(.97%)	(.85%)
	IV Estimate, With School Calendar As An Instrument			
10% Wage Increase (τ)	2.36%	2.69%	2.14%	2.64%
	(.55%)	(.53%)	(.60%)	(.55%)
	OLS Estimate			
10% Wage Increase (δ)	3.62%	3.63%	3.56%	3.63%
	(.02%)	(.02%)	(.02%)	(.02%)
Control for Birth State & Age?	Y	Y	Y	Y
Control for State of Residence	N	Y	N	N
Control for Household Composition	N	N	Y	N
Control for Birth State Trends?	N	N	N	Y

Controls are identical to Table 20

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In Tables 21, I use instrumental variables to create a policy experiment: wages for one child increase, but wages for the rest of the family are held fixed. I find that increasing wages by 10% increases automobile ownership by 2%-4%. This is similar to the OLS estimates. The most likely explanation for the similarity that automobiles are a good substitute for leisure time since driving is much faster than taking a bus or walking. Accordingly, cars are more useful to people who face a high opportunity cost for leisure, regardless of their income level.

Table 22: IV Regression of Transfers Received By Parents on a 10% Wage Increase For Their Children, Using School Calendar As An Instrument

$$\text{Pesos Received}_p = m^*X_j + \xi^* w_f + \theta^*(w_j - w_f) + \varepsilon_p$$

	Dependent variable: Transfer Received by Mother From Family Abroad			
10% Wage Increase for Children (θ)	26.81 Ps.	27.50 Ps.	26.21 Ps.	24.13 Ps.
	(14.55)	(13.83)	(14.10)	(13.99)
	Dependent variable: Transfer Received by Mother From Family in Mexico			
10% Wage Increase for Children (θ)	90.06 Ps.	89.59 Ps.	112.93 Ps.	87.66 Ps.
	(18.08)	(18.03)	(17.57)	(18.05)
	Dependent variable: Transfer Received by Father from Family Abroad			
10% Wage Increase for Children (θ)	45.45 Ps.	46.99 Ps.	45.71 Ps.	42.65 Ps.
	(19.86)	(20.02)	(19.69)	(19.88)
	Dependent variable: Transfer Received by Father from Family In Mexico			
10% Wage Increase for Children (θ)	110.30 Ps.	110.11 Ps.	110.40 Ps.	109.44 Ps.
	(23.18)	(23.14)	(23.07)	(23.25)
Control for Birth State, # Children and Mean Age Children?	Y	Y	Y	Y
Control for State of Residence?	N	Y	N	N
Control for Mother's Age?	N	N	Y	N
Control for Mother's Education	N	N	N	Y

In all specifications, I control for the mean age of children over 25 with a dummy for each year of average age, control for the number of children over 25. I calculate average ages by assuming that children are spaced exactly two years apart. For example, if a woman has 10 children, and her youngest child is 16, then 5 children over 25, with an average age of 31. Couples who do not report valid data on transfers or family size, or who have more than 15 children are excluded. Observations are weighted by the sample weights given in the census, and clustered by state-age cells.

In Table 22, I use instrumental variables to create a policy experiment: wages for adult children increase while holding parents' wages are held fixed. Using school calendar as an instrument, I find that parents get about 275 pesos a month if their children have 10% higher wages. This transfer is sufficient to raise parents' consumption by 7%.

Table 23: IV Regression of Transfers Received By Parents on a 10% Wage Increase for Their Children, Using Temperature As An Instrument

$$\text{Pesos Received}_p = m^*X_j + \xi^* w_f + \theta^*(w_j - w_f) + \varepsilon_p$$

	Dependent variable: Transfer Received by Mother From Family Abroad			
10% Wage Increase for Children (θ)	24.65 Ps. (19.18)	26.18 Ps. (19.12)	26.21 Ps. (19.14)	21.32 Ps. (19.16)
	Dependent variable: Transfer Received by Mother from Family In Mexico			
10% Wage Increase for Children (θ)	52.34 Ps. (18.67)	53.01 Ps. (18.58)	49.21 Ps. (18.67)	51.30 Ps. (18.50)
	Dependent variable: Transfer Received by Father from Family Abroad			
10% Wage Increase for Children (θ)	47.43 Ps. (25.21)	48.72 Ps. (25.39)	46.84 Ps. (25.18)	42.46 Ps. (25.36)
	Dependent variable: Transfer Received by Father from Family In Mexico			
10% Wage Increase for Children (θ)	97.32 Ps. (30.94)	98.25 Ps. (30.75)	93.86 Ps. (30.77)	98.92 Ps. (30.89)
Control for Birth State, # Children and Mean Age Children?	Y	Y	Y	Y
Control for State of Residence?	N	Y	N	N
Control for Mother's Age?	N	N	Y	N
Control for Mother's Education	N	N	N	Y

Controls are identical to Table 22

In Table 23, I use instrumental variables to create a policy experiment: wages for adult children increase while parent's wages are held fixed. Using temperature as an instrument, I find that parents get about 225 pesos a month if their children have 10% higher wages. This transfer is sufficient to raise parents' consumption by 6%.

Appendix 1

Comparison of the Consumption Smoothing Over Life-Cycle and Within Families

In the lifecycle model, a person lives for T periods. In period t, the individual earns a wage w_t and consumes a bundle of consumption and leisure $(c_t^1, \ldots c_t^m, L_t)$. For simplicity, I assume a person has 1 unit of time total in every period, all consumption goods are always priced at 1, the interest rate for borrowing and lending is always r, and the discount rate is always ρ. We can write the individual's maximization problem as:

$$Max \sum_{t=1}^{T} \rho^{t-1} u(c_t^1, \ldots c_t^m, L_t) \text{ subject to budget constraint:}$$
$$\sum_{t=1}^{T} (1+r)^{1-t} (c_t^1 + .. + c_t^m) = \sum_{t=1}^{T} (1+r)^{1-t} w_t (1-L_t)$$

We can then solve this to get first order conditions:

$$(\partial u_t / \partial c_t^r) = (\partial u_s / \partial c_s^r) / \left(\rho^{t-s} * (1+r)^{t-s}\right) \text{ for any time periods t \& s}$$
$$(\partial u_t / \partial L_t) = (w_t / w_s) * (\partial u_s / \partial L_s) / \left(\rho^{t-s} * (1+r)^{t-s}\right) \;\; \& \;\; (\partial u_t / \partial c_t^r) = (1/w_t) * (\partial u_t / \partial L_t)$$

In the risk sharing model, there are n people living for a single period. Individual j earns a wage w_j and consumes a bundle of consumption and leisure $(c_j^1, \ldots c_j^m, L_j)$. For simplicity, I assume each person has 1 unit of time total in every period, all consumption goods are always priced at 1, and the social planner weights every person's utility equally. We can write the social planner's maximization problem as:

$$Max \sum_{j=1}^{n} u(c_j^1, \ldots c_j^m, L_j) \text{ subject to budget constraint: } \sum_{j=1}^{n} (c_j^1 + .. + c_j^m) = \sum_{j=1}^{n} w_j (1-L_j)$$

We can then solve this to get first order conditions:

$$(\partial u_j / \partial c_j^r) = (\partial u_k / \partial c_k^r) \text{ for any people j and k}$$
$$(\partial u_j / \partial L_j) = (w_j / w_k) * (\partial u_k / \partial L_k) \; \& \; (\partial u_j / \partial c_j^r) = (1/w_j) * (\partial u_j / \partial L_j)$$

Except for the discounting in the lifecycle model, these two first order conditions are very similar. If assume that $\rho = 1/(1+r)$, they are identical. The similarity is not particularly surprising: both models study consumption smoothing. The lifecycle model studies consumption smoothing across time. The risk sharing model studies consumption smoothing over possible state of the world.

There is a rich empirical literature studying labor supply elasticity in the lifecycle model. In the lifecycle model, there are two possible policy experiments to study: first, raise a person's wages temporarily, while holding lifetime wages fixed. This is known as the Frisch labor supply elasticity. Oettinger (1999) and Fehr and Gotte (2002) used wage variation caused by demand shocks[45] to get Frisch labor supply elasticity of .5-.65. Mulligan (1998) used long-term wage variation caused by the lifecycle to get a Frisch labor supply elasticity of .57.[46] Second, raise a person's wages over their whole lifetime. This is known as the Marshallian elasticity. In a survey of the literature by Kimball and Shapiro (2003) finds Marshallian labor supply elasticity close to 0. Results for Frisch and Marshallian elasticity are similar in a survey of the literature by Browning, Hansen and Heckman (1999)

How does my estimate of within family labor supply compare to the Marshallian and Frisch elasticities? In Tables 10 and 11, I use instrumental variables to estimate a within family labor supply elasticity of about .4. In Tables 14, I use a sample of brothers to estimate a within family labor supply elasticity of about .35-.4. These numbers are similar in magnitude to the Frisch labor supply elasticities estimated above, providing strong evidence for significant risk sharing within a family[47]. In contrast, the OLS regression of labor supply on wages finds labor supply elasticity less than .1, similar to the Marshallian elasticity. This is consistent with little risk sharing across families.

[45] Oettinger studied labor supply for baseball vendors and used predicted attendance as a measure of wages. Fehr and Gotte created an artificial demand shock by paying some messengers more in the short term.

[46] Taken from page 38 for prime-age men.

[47] Alternatively, there may be both incomplete risk sharing within a family and also incomplete credit markets.

Appendix 2

Corner Solution For Transfers, Consumption and Labor Supply

Assume a general utility function with m consumption goods and one leisure good: $\text{u}(c_j^1,....c_j^m,L_j)$. The utility function is continuous, smooth, and concave everywhere. For simplicity, I assume that the price of the consumptions goods are all fixed at 1, and they are all normal and separable. However, I do not assume that consumption and leisure are separable. Some goods may be complements to leisure and other goods may be substitutes.

Suppose that there are n children in a family. Child j receives a wage of w_j and 1 unit of time to allocate between consumption and leisure. After a child works, he gives a transfer $t_j(w_1...w_n)$ to his parent. Children are altruistic towards their parent, so that their complete utility is $\text{U}_\text{j}\text{=u}(c_j^1,....c_j^m,L_j)\text{+}\alpha\text{u}(c_p^1,...c_p^m,L_p)$. I assume that the family is at a corner solution. Therefore, every child gives a transfer of 0 to his parent.

Lemma 1: $(\partial t_j/\partial w_k)=0,\ (\partial c_j^r/\partial w_k)=0,\ \&\ (\partial L_j/\partial w_k)=0$

Child j's problem can be written as:

$$\text{Max u}(c_j^1,...c_j^m,L_j)+\alpha(c_p^1,...c_p^m,L_p)\text{ subject to:}$$

$$\text{Child j's budget constraint: } c_j^1+..+c_j^m=w_j(1-L_j)-t_j \quad (1.1)$$

$$\text{Parent's budget constraint: } c_p^1+..+c_p^m=w_p(1-L_p)+t_1+....+t_n$$

By assumption, $t_j=0$ no matter what value w_j or w_k has. Therefore, $(\partial t_j/\partial w_k)\text{=}0$.

Because transfers are always 0, we can simplify child j's problem to get:

$$(1.2)\quad \begin{array}{l}\text{Max u}(c_j^1,...c_j^m,L_j)+\alpha(c_p^1,...c_p^m,L_p)\text{ subject to:}\\ \text{Child j's budget constraint: } c_j^1+..+c_j^m=w_j(1-L_j)\end{array}$$

Child j has a very straightforward utility function: he cares about his own leisure and consumption, and his parent's total utility. Therefore consumption and leisure for child j depend only on own wage, and transfer sent to the parent.

(1.3) $(\partial L_j/\partial w_k)\text{=}(\partial L_j/\partial t_j)\text{*}(\partial t_j/\partial w_k)\text{=}(\partial L_j/\partial t_j)\text{*}0\text{=}0$

(1.4) $(\partial c_j^r/\partial w_k)\text{=}(\partial c_j^r/\partial t_j)\text{*}(\partial t_j/\partial w_k)\text{=}(\partial c_j^r/\partial t_j)\text{*}0\text{=}0$

Lemma 2: $(\partial L_j / \partial w_j) - (\partial L_j / \partial w_k)$ is ambiguous

Child j's problem can be written as:

$$\begin{aligned}
&\text{Max } u(c_j^1, \ldots c_j^m, L_j) + \alpha(c_p^1, \ldots c_p^m, L_p) \text{ subject to:} \\
(2.1) \quad &\text{Child j's budget constraint: } c_j^1 + .. + c_j^m = w_j(1 - L_j) - t_j \\
&\text{Parent's budget constraint: } c_p^1 + .. + c_p^m = w_p(1 - L_p) + t_1 + ... + t_n
\end{aligned}$$

By assumption, $t_j = 0$. We can simplify child j's problem as:

$$(2.2) \quad \begin{aligned}
&\text{Max } u(c_j^1, \ldots c_j^m, L_j) + \alpha(c_p^1, \ldots c_p^m, L_p) \text{ subject to:} \\
&\text{Child j's budget constraint: } c_j^1 + .. + c_j^m = w_j(1 - L_j)
\end{aligned}$$

This produces first order conditions:

(2.3) $(\partial \mathrm{u_j} / \partial c_j^s) = (1/w_j)(\partial \mathrm{u_j} / \partial L_j) = \lambda_j \;\; \forall$ good s

We can then differentiate (2.3) with respect to w_j to get Second order conditions:

(2.4) $(\partial \mathrm{u_j^2} / \partial c_j^s \partial w_j) = (\partial \lambda_j / \partial w_j)$ & $(\partial \mathrm{u_j^2} / \partial L_j \partial w_j) = \lambda_j + w_j(\partial \lambda_j / \partial w_j)$

For smooth functions, $(\partial f / \partial x \partial y) = (\partial f / \partial y \partial x)$, so we can differentiate in reverse to get more information.

(2.5) $(\partial u_j / \partial w_j) = \sum_{r=1}^{m} (\partial \mathrm{u_j} / \partial c_j^r)(\partial c_j^r / \partial w_j) + (\partial \mathrm{u_j} / \partial L_j)(\partial L_j / \partial w_j)$

(2.6) $(\partial u_j^2 / \partial w_j \partial L_j) = \sum_{r=1}^{m} (\partial \mathrm{u_j} / \partial c_j^r \partial L_j)(\partial c_j^r / \partial w_j) + (\partial \mathrm{u_j^2} / \partial L_j^{\,2})(\partial L_j / \partial w_j)$

(2.7) $(\partial u_j^2 / \partial w_j \partial c_j^s) = \sum_{r=1}^{m} (\partial \mathrm{u_j} / \partial c_j^r \partial c_j^s)(\partial c_j^r / \partial w_j) + (\partial \mathrm{u_j^2} / \partial L_j \partial c_j^s)(\partial L_j / \partial w_k) \;\; \forall$ good s

By assumption, the utility from different consumption goods is separable. So, we can simplify (2.7) to get:

(2.8) $(\partial u_j^2 / \partial w_j \partial c_j^s) = (\partial \mathrm{u_j^2} / \partial^2 c_j^s)(\partial c_j^s / \partial w_j) + (\partial \mathrm{u_j^2} / \partial L_j \partial c_j^s)(\partial L_j / \partial w_j) \;\; \forall$ good s

Combining (2.8) and (2.4), we get:

$$(2.9)\quad \begin{aligned}&(\partial\lambda_j/\partial w_j) = (\partial \mathrm{u}_\mathrm{j}^2/\partial^2 c_j^s)(\partial c_j^s/\partial w_j) + (\partial \mathrm{u}_\mathrm{j}^2/\partial L_j \partial c_j^s)(\partial L_j/\partial w_j) \rightarrow\\ &(\partial c_j^s/\partial w_j) = \big((\partial\lambda_j/\partial w_j) - (\partial \mathrm{u}_\mathrm{j}^2/\partial L_j \partial c_j^s)(\partial L_j/\partial w_j)\big)/(\partial \mathrm{u}_\mathrm{j}^2/\partial^2 c_j^s)\end{aligned}$$

Similarly, we can combine (2.6) and (2.4) to get:

$$(2.10)\quad w_j(\partial\lambda_j/\partial w_j) + \lambda_j = \sum_{r=1}^{m}(\partial \mathrm{u}_\mathrm{j}/\partial c_j^r \partial L_j)(\partial c_j^r/\partial w_j) + (\partial \mathrm{u}_\mathrm{j}^2/\partial L_j^2)(\partial L_j/\partial w_j)$$

If we combine (2.10) and (2.9), we get:

$$(2.11)\quad \begin{aligned}&\sum_{r=1}^{m}\big((\partial \mathrm{u}_\mathrm{j}/\partial c_j^r \partial L_j)/(\partial \mathrm{u}_\mathrm{j}^2/\partial^2 c_j^r)\big)\big((\partial\lambda_j/\partial w_j) - (\partial \mathrm{u}_\mathrm{j}^2/\partial L_j \partial c_j^r)(\partial L_j/\partial w_j)\big) +\\ &(\partial \mathrm{u}_\mathrm{j}^2/\partial L_j^2)(\partial L_j/\partial w_j) = w_j(\partial\lambda_j/\partial w_j) + \lambda_j\end{aligned}$$

$$(2.12)\quad \begin{aligned}&(\partial L_j/\partial w_j) = \left((\partial\lambda_j/\partial w_j)\left(w_j - \sum_{r=1}^{m}(\partial \mathrm{u}_\mathrm{j}/\partial c_j^r \partial L_j)/(\partial \mathrm{u}_\mathrm{j}^2/\partial^2 c_j^r)\right) + \lambda_j\right)/\\ &\left((\partial \mathrm{u}_\mathrm{j}^2/\partial L_j^2) - \sum_{r=1}^{m}(\partial \mathrm{u}_\mathrm{j}/\partial c_j^r \partial L_j)^2/(\partial \mathrm{u}_\mathrm{j}^2/\partial^2 c_j^r)\right)\end{aligned}$$

Because utility is concave, $(\partial\lambda_j/\partial w_j) < 0$, $\lambda_j > 0$ & $\left(w_j - \sum_{r=1}^{m}(\partial \mathrm{u}_\mathrm{j}/\partial c_j^r \partial L_j)/(\partial \mathrm{u}_\mathrm{j}^2/\partial^2 c_j^r)\right) > 0$. Because all consumption goods and leisure are normal, $\left((\partial \mathrm{u}_\mathrm{j}^2/\partial L_j^2) - \sum_{r=1}^{m}(\partial \mathrm{u}_\mathrm{j}/\partial c_j^r \partial L_j)^2/(\partial \mathrm{u}_\mathrm{j}^2/\partial^2 c_j^r)\right) < 0$.

We can break (2.12) into two parts. The first part is the income effect:

$$(\partial\lambda_j/\partial w_j)\left(w_j - \sum_{r=1}^{m}(\partial \mathrm{u}_\mathrm{j}/\partial c_j^r \partial L_j)/(\partial \mathrm{u}_\mathrm{j}^2/\partial^2 c_j^r)\right)/\left((\partial \mathrm{u}_\mathrm{j}^2/\partial L_j^2) - \sum_{r=1}^{m}(\partial \mathrm{u}_\mathrm{j}/\partial c_j^r \partial L_j)^2/(\partial \mathrm{u}_\mathrm{j}^2/\partial^2 c_j^r)\right)$$

The income effect is (-)(+)/(-) = (+). The second part is the substitution effect:

$$\lambda_j/\left((\partial \mathrm{u}_\mathrm{j}^2/\partial L_j^2) - \sum_{r=1}^{m}(\partial \mathrm{u}_\mathrm{j}/\partial c_j^r \partial L_j)^2/(\partial \mathrm{u}_\mathrm{j}^2/\partial^2 c_j^r)\right)$$

The substitution effect is (+)/(-) = (-)

The net effect of wages on labor supply is the income effect and the substitution effect. This effect is theoretically ambiguous, and the solution depends on the exact utility function.

Lemma 3: $\sum_{r=1}^{m}(\partial c_j^r/\partial w_j) > 0$

According to (2.4) and (2.8) from Lemma 2, (3.1) $(\partial \mathrm{u}_j^2/\partial c_j^s \partial w_j) = (\partial \lambda_j / \partial w_j)$ $\forall$ good s & $(\partial \mathrm{u}_j^2/\partial L_j \partial w_j) = \lambda_j + w_j(\partial \lambda_j / \partial w_j)$

(3.2) $(\partial u_j^2 / \partial w_j \partial c_j^s) = (\partial \mathrm{u}_j^2 / \partial^2 c_j^s)(\partial c_j^s / \partial w_j) + (\partial \mathrm{u}_j^2 / \partial L_j \partial c_j^s)(\partial L_j / \partial w_j)$ $\forall$ good s

We can them combine to get:

(3.3) $(\partial c_j^s / \partial w_j) = \big((\partial \lambda_j / \partial w_j) \text{-} (\partial \mathrm{u}_j^2 / \partial L_j \partial c_j^s)(\partial L_j / \partial w_j)\big) / (\partial \mathrm{u}_j^2 / \partial^2 c_j^s)$

This is theoretically ambiguous: $(\partial \lambda_j / \partial w_j) < 0$, $(\partial \mathrm{u}_j^2 / \partial L_j \partial c_j^s) = ?$, $(\partial L_j / \partial w_j) = ?$ and $(\partial \mathrm{u}_j^2 / \partial^2 c_j^s) = ?$. Therefore, $(\partial c_j^s / \partial w_j) = \big((-) \text{-} (?)(?)\big)/(-) = ?$.

However, we can determine what happens to aggregate consumption. By assumption, there are no transfers, so the budget constraint is simply:

(3.4) $\sum_{r=1}^{m} c_j^r = w_j * (1 - L_j) \rightarrow \sum_{r=1}^{m} \partial c_j^r / \partial w_j = (1 - L_j) - w_j(\partial L_j / \partial w_j)$

Therefore, $\sum_{r=1}^{m} \partial c_j^r / \partial w_j < 0$ if and only if $(1 - L_j)/w_j < (\partial L_j / \partial w_j)$

By assumption, both consumption and leisure are normal goods. Therefore,

(3.5) $1/w_j > (\partial L_j / \partial I_j) > 0$.

In other words, if give child j an extra dollar, he we spend some of his money on leisure and some of his money on consumption.

We can decompose labor supply elasticity into two parts.

(3.6) $(\partial L_j / \partial w_j) = (\partial L_j / \partial I_j) * (\partial I_j / \partial w_j) + (\partial L_j / \partial w_j)_H$

Combining (3.5) and (3.6), we get:

(3.7) $(\partial L_j / \partial w_j) < (1/w_j) * (1 - L) + (\partial L_j / \partial w_j)_H$

$(\partial L_j / \partial w_j)_H$ is the pure substitution effect of changing wages. It is always negative, because higher wage raise the opportunity cost of leisure. We can simplify (3.7) to get:

(3.8) $(\partial L_j / \partial w_j) < (1 - L)/w_j \rightarrow \sum_{r=1}^{m} \partial c_j^r / \partial w_j > 0$

Appendix 3

Interior Solution For Transfers, Consumption and Labor Supply

Assume a general utility function with m consumption goods and one leisure good: $\mathrm{u}(c_j^1,....c_j^m,L_j)$. The utility function is continuous, smooth, and concave everywhere. For simplicity, I assume that the price of the consumptions goods are all fixed at 1, and they are all normal and separable. However, I do not assume that consumption and leisure are separable. Some goods may be complements to leisure, and other goods may be substitutes.

Suppose that there are n children in a family. Child j receives a wage of w_j and 1 unit of time to allocate between consumption and leisure. After a child work, he gives a transfer $t_j(w_1...w_n)$ to his parent. Children are altruistic towards their parent, so that $\mathrm{U_j}=\mathrm{u}(c_j^1,....c_j^m, L_j)+\alpha\mathrm{u}(c_p^1,...c_p^m, L_p)$. I assume that the family is at an interior solution, so that every children gives a positive transfer to his or her parent. I also assume that children move simultaneously – so that they cannot change their behavior in response to sibling's behavior.

Lemma 1: $\left((\partial L_j/\partial w_j)-(\partial L_j/\partial w_k)\right)<0$ & $\left((\partial c_j^r/\partial w_j)-(\partial c_j^r/\partial w_k)\right)$ is ambiguous

Child j's problem can be written as:

$$\text{Max } \mathrm{u}(c_j^1,...c_j^m,L_j)+\alpha(c_p^1,...c_p^m,L_p) \text{ subject to:}$$

$$\text{Child j's budget constraint: } c_j^1+..+c_j^m=w_j(1-L_j)-t_j$$

$$\text{Parent's budget constraint: } c_p^1+..+c_p^m=w_p(1-L_p)+\sum_{k\neq j}^{n}t_k+t_j \tag{1.1}$$

Child j picks $(c_j^1,...c_j^m,L_j)$, $(c_p^1,...c_p^m,L_p)$ and t_j

However, transfers by the other children, $\sum_{k\neq j}^{n}t_k$ are a fixed constant

Because child j views the other child's transfers as fixed, this is equivalent to all children moving simultaneously. This version of the public good problem is often called the Cournot-Nash model. This solution was first introduced by Warr in 1983 but has been studied by many authors since.

We can solve child j's utility problem to get first order conditions

$$(\partial\mathrm{u_j}/\partial c_j^r)=w_p(\partial\mathrm{u_p}/\partial c_p^r)=\lambda_\mathrm{p} \;\&\; w_j(\partial\mathrm{u_j}/\partial c_j^r)=(\partial\mathrm{u_j}/\partial L_j)=\lambda_\mathrm{j} \;\&\; \lambda_j=\alpha\lambda_\mathrm{p}. \tag{1.2}$$

Because all children in the family are at the interior solution, we can rewrite (1.2) as:

$$(1.3) \qquad (\partial \mathrm{u}_j / \partial c_j^r) = \lambda = (\partial \mathrm{u}_k / \partial c_k^r) \;\&\; (\partial \mathrm{u}_j / \partial L_j) = w_k \lambda = \; (\partial \mathrm{u}_k / \partial L_k)$$

We can then differentiate (1.3) with respect to w_j to get second order conditions:

$$(1.4) \qquad (\partial \mathrm{u}_j^2 / \partial c_j^r \partial w_j) = (\partial \lambda / \partial w_j) \;\&\; (\partial \mathrm{u}_j^2 / \partial L_j \partial w_j) = \lambda + w_j (\partial \lambda / \partial w_j)$$

Similarly, we can differentiate (1.3) with respect to w_k to get second order conditions:

$$(1.5) \qquad (\partial \mathrm{u}_j^2 / \partial c_j^r \partial w_k) = (\partial \lambda / \partial w_k) \;\&\; (\partial \mathrm{u}_j^2 / \partial L_j \partial w_k) = w_j (\partial \lambda / \partial w_k)$$

For smooth functions, $(\partial f / \partial x \partial y) = (\partial f / \partial y \partial x)$, so we can differentiate in reverse to get more information.

$$(1.6) \; (\partial u_j / \partial w_k) = \sum_{r=1}^{m} (\partial \mathrm{u}_j / \partial c_j^r)(\partial c_j^r / \partial w_k) + (\partial \mathrm{u}_j / \partial L_j)(\partial L_j / \partial w_k) \; \forall \text{ siblings j \& k}$$

$$(1.7) \; (\partial u_j^2 / \partial w_k \partial L_j) = \sum_{r=1}^{m} (\partial \mathrm{u}_j / \partial c_j^r \partial L_j)(\partial c_j^r / \partial w_k) + (\partial \mathrm{u}_j^2 / \partial L_j{}^2)(\partial L_j / \partial w_k) \; \forall \text{ siblings j and k}$$

$$(1.8) \; (\partial u_j^2 / \partial w_k \partial c_j^s) = \sum_{r=1}^{m} (\partial \mathrm{u}_j / \partial c_j^r \partial c_j^s)(\partial c_j^r / \partial w_k) + (\partial \mathrm{u}_j^2 / \partial L_j \partial c_j^s)(\partial L_j / \partial w_k)$$
$$\forall \text{ siblings j \& k and good s}$$

By assumption, the utility from different consumption goods is separable. So, we can simplify (1.8) to get:

$$(1.9) \; (\partial u_j^2 / \partial w_k \partial c_j^s) = (\partial \mathrm{u}_j^2 / \partial^2 c_j^s)(\partial c_j^s / \partial w_k) + (\partial \mathrm{u}_j^2 / \partial L_j \partial c_j^s)(\partial L_j / \partial w_k)$$
$$\forall \text{ siblings j \& k and good s}$$

Combining (1.9) and (1.5), we get:

$$(1.10) \; \begin{aligned} &(\partial \lambda / \partial w_k) = (\partial \mathrm{u}_j^2 / \partial^2 c_j^s)(\partial c_j^s / \partial w_k) + (\partial \mathrm{u}_j^2 / \partial L_j \partial c_j^s)(\partial L_j / \partial w_k) \rightarrow \\ &(\partial c_j^s / \partial w_k) = \left((\partial \lambda / \partial w_k) - (\partial \mathrm{u}_j^2 / \partial L_j \partial c_j^s)(\partial L_j / \partial w_k) \right) / (\partial \mathrm{u}_j^2 / \partial^2 c_j^s) \end{aligned}$$

We can also rewrite (1.10) as:

$$(1.11) \; (\partial c_j^s / \partial w_j) - (\partial c_j^s / \partial w_k) = -\left((\partial \mathrm{u}_j^2 / \partial L_j \partial c_j^s) / (\partial \mathrm{u}_j^2 / \partial^2 c_j^s) \right) \left((\partial L_j / \partial w_j) - (\partial L_j / \partial w_k) \right)$$

Similarly, we can combine (1.7), (1.3) and (1.4) to get:

$$(1.12)\quad \begin{aligned} &w_j(\partial\lambda/\partial w_k) = \sum_{r=1}^{m}(\partial \mathrm{u_j}/\partial c_j^r \partial L_j)(\partial c_j^r/\partial w_k) + (\partial \mathrm{u_j^2}/\partial L_j^2)(\partial L_j/\partial w_k) \text{ for } \mathrm{j} \neq \mathrm{k} \\ &w_j(\partial\lambda/\partial w_j) + \lambda = \sum_{r=1}^{m}(\partial \mathrm{u_j}/\partial c_j^r \partial L_j)(\partial c_j^r/\partial w_j) + (\partial \mathrm{u_j^2}/\partial L_j^2)(\partial L_j/\partial w_j) \end{aligned}$$

If we combine (1.10) and (1.12), we get:

(1.13)

$$\sum_{r=1}^{m}\Big((\partial\lambda/\partial w_k)(\partial \mathrm{u_j}/\partial c_j^r \partial L_j) - (\partial \mathrm{u_j^2}/\partial L_j \partial c_j^r)^2(\partial L_j/\partial w_k)\Big)/(\partial \mathrm{u_j^2}/\partial^2 c_j^s) + (\partial \mathrm{u_j^2}/\partial L_j^2)(\partial L_j/\partial w_k) =$$

$w_j(\partial\lambda/\partial w_k)$ for $\mathrm{j} \neq \mathrm{k}$

(1.14)

$$\sum_{r=1}^{m}\Big((\partial\lambda/\partial w_j)(\partial \mathrm{u_j}/\partial c_j^r \partial L_j) - (\partial \mathrm{u_j^2}/\partial L_j \partial c_j^r)^2(\partial L_j/\partial w_j)\Big)/(\partial \mathrm{u_j^2}/\partial^2 c_j^s) + (\partial \mathrm{u_j^2}/\partial L_j^2)(\partial L_j/\partial w_j) =$$

$w_j(\partial\lambda/\partial w_j) + \lambda$

By assumption, every child in the family has identical utility functions, and wage shocks are small. Therefore, the family is symmetrical and $(\partial\lambda/\partial w_k)$ =$(\partial\lambda/\partial w_j)$. We can thereby combine (1.13) and (1.14) to get:

(1.15)

$$\sum_{r=1}^{m}\Big((\partial \mathrm{u_j^2}/\partial L_j \partial c_j^r)^2/(\partial \mathrm{u_j^2}/\partial^2 c_j^s)\Big)\Big((\partial L_j/\partial w_j) - (\partial L_j/\partial w_k)\Big) + (\partial \mathrm{u_j^2}/\partial L_j^2)\Big((\partial L_j/\partial w_j) - (\partial L_j/\partial w_k)\Big) = \lambda \rightarrow$$

$$\Big((\partial L_j/\partial w_j) - (\partial L_j/\partial w_k)\Big) = \lambda / \left((\partial \mathrm{u_j^2}/\partial L_j^2) - \sum_{r=1}^{m}\Big((\partial \mathrm{u_j^2}/\partial L_j \partial c_j^r)^2/(\partial \mathrm{u_j^2}/\partial^2 c_j^s)\Big)\right)$$

Because leisure is a normal good, $(\partial \mathrm{u_j^2}/\partial L_j^2) < \sum_{r=1}^{m}\Big((\partial \mathrm{u_j^2}/\partial L_j \partial c_j^r)^2/(\partial \mathrm{u_j^2}/\partial^2 c_j^s)\Big)$, and the utility function is monotonically increasing such that $\lambda>0$. Therefore,

(1.16) $(\partial L_j/\partial w_j) - (\partial L_j/\partial w_k) = (+)/(-) \rightarrow (\partial L_j/\partial w_j) < (\partial L_j/\partial w_k)$

Lemma 2: $\Big((\partial c_j^r/\partial w_j) - (\partial c_j^r/\partial w_k)\Big)$ is ambiguous

According to (1.11):

(2.1) $(\partial c_j^s/\partial w_j) - (\partial c_j^s/\partial w_k) = -\Big((\partial \mathrm{u_j^2}/\partial L_j \partial c_j^s)/(\partial \mathrm{u_j^2}/\partial^2 c_j^s)\Big)\Big((\partial L_j/\partial w_j) - (\partial L_j/\partial w_k)\Big)$

Equation (2.1) is inherently ambiguous. In Lemma 1 $\left((\partial L_j / \partial w_j) - (\partial L_j / \partial w_k)\right) < 0$, and $(\partial \mathrm{u}_\mathrm{j}^2 / \partial^2 c_j^s) < 0$ for all concave utility functions. But the cross-partial, $(\partial \mathrm{u}_\mathrm{j}^2 / \partial L_j \partial c_j^s)$, can be either positive or negative. If $(\partial \mathrm{u}_\mathrm{j}^2 / \partial L_j \partial c_j^s)$ >0, then good s is a complement to leisure. In that case, $(\partial c_j^s / \partial w_j) - (\partial c_j^s / \partial w_k) = (-)(+)/(-)*(-) = (-)$. If $(\partial \mathrm{u}_\mathrm{j}^2 / \partial L_j \partial c_j^s)$ <0, then good s is a substitute for leisure. In that case, $(\partial c_j^s / \partial w_j) - (\partial c_j^s / \partial w_k) = (-)(-)/(-)*(-) = (+)$

Appendix 4

Effects of Emigration to the United States

Lacuesta (2004) reports that approximately 10% of the population born in Mexico currently lives in the United States. The percentage is even higher for working aged men. Accordingly, the Mexican census is a selected sample of the total Mexican population: it excludes men who have chosen to leave. There is some research studying the differences between movers and stayers.

Emigrants have slightly more education than men who stay in Mexico (Chiquar and Hanson 2002). In the 2000 US Census, white men 20-74 born in Mexico[48] report an average of 8.6 years of education,[49] and in the 2000 Mexican census, non-Indian men 20-74 report an average of 7.9 years of education. I also find that men who receive negative education shocks from school calendar changes are less likely to disappear between the 1970 and 2000 Mexican Census. The difference is likely caused by emigration because results are similar when I focus on men under 65, who are unlikely to have experienced significant mortality[50]. On the other hand, education shocks from temperature have no effect on cohort size. And recent research by Ibarran and Lubotsky (2005) find that migrants to the US are less educated than Mexicans who stay in Mexico.[51] Regardless of the sign, the magnitude of the difference is very small.

Emigrants also work less than men who stay in Mexico. Comparing the 2000 US Census and the 2000 Mexican Census, I find Mexican-born men currently living in the United States work 8 hours less per week than Mexicans in Mexico. This may suggest that the two groups have different preferences for leisure. However, another possible explanation is that the two labor markets are simply not comparable. The typical work week in the US is five days and the typical work week in Mexico is six days. Even if emigrants have the same preferences for leisure as men who stay in Mexico, it might be difficult for them to find a job working 48 hours a week.

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[48] This includes men who are imputed a Mexican birth.

[49] This is assuming that people have the midpoint for each education range and years of education are reported accurately. Ibarran and Lubotsky (2005) report that men in the US Census often appear to answer the questions inaccurately, biasing education upwards. The US Census may also undercount illegal immigrants, biasing results.

[50] It is also possible that the difference results from under-counting or improper weighting by the Mexican Census Bureau.

[51] They use average family education to impute education, so it is possible that migrants are well educated men from poorly education families.