A A simple model of risk-sharing

In this section we sketch a simple risk-sharing model to show why the credit and insurance market is an important channel for the transmission of positive income shocks to the entire village. While the model we consider is not new (in fact, it draws heavily from Cochrane (1991), Mace (1991) and Townsend (1994), among others) we need it to formalize the intuitions and to derive the testable hypotheses.

Consider two infinitely lived agents, $i \in \{1, 2\}$, with instantaneous utility function $u_i = (1-\delta)ln(c_i)$, a rate of inter-temporal preference $\delta < 1$, an endowment y_i, no storage technology, and no leisure. Each agent receives a random income $y_i(s)$ that varies in different (finite) states of the world $s \in S$. Each state of the world occurs with a positive probability $\pi(s)$, with $\sum_s \pi(s) = 1$. In each state of the world the sum of the agents' consumption equals the total available resources, $c_1(s) + c_2(s) = y_1(s) + y_2(s) > 0$.

The social planner maximizes a weighted average of the agents' utility functions, where the weights $\lambda \in (0; 1)$ and $(1 - \lambda)$ represent the relative importance of the two agents. In the absence of commitment issues, the maximization problem is:

$$max_{c_1} U = \sum_s \pi(s)[\lambda ln(c_1(s)) + (1 - \lambda)ln(y_1(s) + y_2(s) - c_1(s))]$$

We can derive the optimal consumption levels in each state from the first-order conditions. These are:

$$c_1^*(s) = \lambda(y_1(s) + y_2(s)) \tag{1}$$

$$c_2^*(s) = (1 - \lambda)(y_1(s) + y_2(s)) \tag{2}$$

As well-known, with full risk-sharing consumption depends only on aggregate resources and on the Pareto weights, and not on the individual endowments. The agents smooth consumption making transfers to each other. The optimal transfer in each state of the world is:

$$d^*(s) = y_1(s)(1-\lambda) - y_2(s)\lambda \tag{3}$$

where $d^*(s) > 0$ if $y_1(s) > c_1^*(s)$, in which case agent 1 transfers part of her income to agent 2, and vice versa. This implies that, when the less wealthy agent has a positive income shock, she may make positive transfers to the wealthier agent. For example, suppose the weights are $\lambda = \frac{2}{5}$ and $(1-\lambda) = \frac{3}{5}$. We choose the figures to roughly match the consumption ratios of poor and non-poor in the data. Consider a good state of the world for both agents, but especially for agent 1: $y_1 = 14$ and $y_2 = 16$. Consumption is $c_1^* = \frac{2}{5}(30) = 12$ and $c_2^* = \frac{3}{5}(30) = 18$, therefore agent 1 will transfer $d^* = 2$ to agent 2, despite their negative income differential and the fact that also agent 2 had a good shock.

Suppose agents 1 and 2 represent eligible and ineligible households. Progresa represents a good state of the world for agent 1, increasing the total resources available in treatment villages with respect to the counterfactual state in which Progresa does not exist. The consumption of both agents is a positive function of $y_1(s)$, and agent 1's transfer to agent 2 is a positive function of her income, i.e. $\frac{\partial d^*(s)}{\partial y_1(s)}$ (or, alternatively, the transfer from agent 2 to agent 1 is a negative function of agent 1's income). Therefore, the effect of this exogenous change in $y_1(s)$ is an increase in both $c_2^*(s)$ and $d^*(s)$, from equations (2) and (3). The model shows that, as Progresa increases the income of eligible households while leaving λ and $y_2(s)$ unchanged, the consumption of both eligible and ineligible families will increase, and so will the net transfers to the ineligibles. These results generate our testable hypotheses:

Hp 1: $\frac{\partial c_2^*(s)}{\partial y_1(s)} > 0$. Progresa increases the consumption of ineligible households in treatment villages.

Hp 2: $\frac{\partial d^*(s)}{\partial y_1(s)} > 0$. Progresa increases net transfers to the ineligibles in treatment villages.

B Data creation

In this Appendix we describe how we created some of the relevant variables for our analysis: consumption, transfers and loans, school enrollment, hours of work, earnings, and prices.

B.1 Food consumption

We consider the three data waves collected after the program begins, in November 1998, May 1999, and November 1999. For each of 36 food items, households report the quantity consumed the week before the interview, as well as the quantity purchased and its cost. If expenditure on a particular item is missing, but we know the amount purchased, we consider the village median price. We compute the village price in the following way: we create household-specific prices by dividing the expenditure in food purchased during the last week by the quantity bought. If we have at least 20 household-specific prices per village, we use this information to compute median prices at the village level. Otherwise, we use either median municipality or state price (we use the lowest level of aggregation with at least 20 price observations). Once we have household-specific prices, we multiply them by quantity consumed. We do this because households produce part of the consumed food. Considering only food expenditure would underestimate the amounts actually consumed.

We use November 1998 prices to compute consumption values in May and November 1999 also. Unlike in 1998, in 1999 we know both how much food is purchased and how much is consumed, but we have no direct information on home-produced food. Hence, in order to be consistent between the three waves, we assume that in 1999 all food purchased is consumed if total consumption is smaller or equal than food purchased. If total consumption is greater than purchased goods we apply median prices to the difference, this means that either home-produced food, or food given as a present is evaluated at market prices. Since we could not convert different measurement units in a single one, we only consider those who have bought and consumed food in the same unit (Kilo, Liter or Units). We believe that the absence of measurement conversion does not pose any major problem, since only about 1% of the sample has different measurements for the same food. Lastly, we compute adult equivalents for both food and non-food data. For this purpose, we use the adult equivalence conversion estimated by Di Maro (2004) using Progresa data. According to Di Maro, children consume on average 73% of adults. For example, to estimate individual consumption per adult for a household with one child and one adult, we divide household consumption by 1.73.

An additional issue is how to treat missing observations. We noted that some aliments, which are not staples for rural Mexicans, have a large number of missing observations. Thus, we create three different food expenditure variables, each time dropping all households with missing observations. The first variable is aggregate expenditure in food consumption for all available categories (hence the one with the highest number of missing observations). In this way, we drop about 5% of the sample. The second one excludes industrially produced food (*pastelillos en bolsa*, soft drinks, coffee, sugar, vegetable oil). The third food consumption variable excludes industrially produced food, sliced bread (*pan de caja*), breakfast cereals, fish, and seafood. The results we show in the paper use the first consumption variable. However, they are robust to the use of these alternative variables.

The food consumption variable we use in the paper has the following number of non-missing observations for non-poor: 5003 in November 1998, 3856 in May 1999, and 4286 in November 1999. 371 (i.e. about 7%) households have zero food consumption in November 1998. Only 14 and 3 households have zero food expenditure in the May and November 1999 data, respectively. We drop the households with a food consumption level larger than 10000 *pesos* per adult equivalent per month since they are likely outliers. We do the same for poor households, whose final samples have 11684, 9659, and 10555 households for the three waves. There is a drop in the valid household size in May 1999, supposedly due to a higher proportion of non-responses (this drop is not limited to the consumption variables). However, the proportion of households in treated and control areas is roughly constant over time (for non-poor, this proportion ranges from 38.8% living in control areas in November 1998 to 39.9% in November 1999). Because of this, we believe that the smaller sample size in May 1999 does not pose attrition problems.

B.2 Non-food consumption

For non-food consumption, we also consider the three waves used above. The variable on non-food consumption is only available as expenditure on particular categories of non-food items. Our measure of monthly non-food consumption is the sum of expenditures in: transportation both for adults and children; tobacco; personal and household hygiene; drugs and prescriptions; doctor visits; heating (ie. wood, gas, oil); electricity; clothing and shoes; school items (ie. pencils, books). As for food consumption, we trim the extreme values because of possible measurement error. The value of the expenditure is then converted in real terms by applying the monthly CPI (Bank of Mexico, 2005).

The pre-program difference in non-food consumption between non-poor households in treatment and control villages using March 1998 data is not statistically significant.

B.3 Labor earnings

The 1998 and 1999 surveys report hours of work for the sole sub-set of individuals who have a paid job, unlike the 1997 pre-program one, which collects working hour information for all individuals. In 1997 there is no explicit distinction between paid and unpaid jobs. Thus, in order to create a consistent measure, we excluded self-employed, business owners and *ejidatarios* from the computation of hours of work. We considered as unemployed all individuals who reported not having a job in the previous week (unlike those who said that they have a job but could not work). In case of disagreement (i.e. individuals reporting they do not have a job, but having a positive number of hours worked) we included the reported work time.

We also have data on remunerated informal activities, such as selling products, or preparing products for sale, cooking, cleaning, or ironing, or helping out in some business or in the field, etc. For these activities, we observe earnings, time spent working, as well as costs (with the exception of the 1997 data, for which we have no cost data). We add net earnings from informal activities to the formal jobs.

These variables are very noisy measures of work time and earnings, as at times we have to impute monthly earnings from daily, weekly or annual wages. To limit the number of outliers, we trim the top percentile of the positive values, and we also drop the few negative values.

B.4 Prices

Prices refer to the food and non-food goods used to compute the value of consumption. There are 57 different goods, but only food prices are available before the program begins, in March 1998. Thus, we use the 36 food prices available both before and during the program implementation to provide double-difference (DD) estimates of the effect of Progresa. In November 1998 and May 1999 we have up to two prices for each good. When two different prices for the same good are available, we compute the mean village price. Table B1 provides a list of the goods used in the DD analysis of the program effect presented in Table B2.

We find a small positive effect on some food prices in November 1998. Prices of onions (p2), lemons (p8), eggs (p26), and coffee (p34) are significantly higher in treatment than in control areas. At the same time, though, the price of fish (p23) is significantly lower. Despite the fact that onions, eggs, and coffee are commonly consumed foods (Hoddinott *et al.*, (2000)), we do not expect these price changes to increase the cost of the food basket substantially, because prices of staples such as rice, beans, corn, and chicken do not change. Second, there is no price change in the later waves. Third, if we consider the pooled waves, the prices of 6 items increase, while the prices of 3 goods decrease in the observed time, out of a total of 36 items by 3 waves. This amounts to roughly 8% of good prices changing. We believe that, perhaps with the exception of a minor price increase for some goods in the end of 1998, Progresa does not significantly change prices in treatment areas.[1]

As a further robustness check, we considered all 57 different (food and non-food) goods available in the 3 waves collected after the beginning of the program. We pooled prices, creating a price basket that gives equal weight of one to each good. We then regressed this synthetic price indicator on a dummy for treatment and control villages, obtaining cross sectional estimates of the effect of Progresa on prices. Also in this case we reject the hypothesis that prices differ significantly between the two village groups.[2]

[1]There is a large number of missing observations. Since there are 506 villages observed in 4 different points in time, each price should have about 2000 observations. Instead, the non-missing observations range between 313 and 1375.

[2]Results available upon request.

Table A1: ITEs on 1999 food log-consumption by category per adult equivalent

	Fruits and vegetables	Grains and cereals	Meat, fish, and dairy products	Industrial products
ITE May	0.108	0.073	-0.030	0.031
	[0.043]**	[0.035]**	[0.055]	[0.046]
Obs.	3791	3829	3560	3797
ITE Nov.	0.065	0.051	0.108	0.033
	[0.038]*	[0.029]*	[0.050]**	[0.043]
Obs.	4254	4277	4064	4267

Log of monthly pesos per adult equivalent.
Standard errors in brackets clustered at the village level.
***, **, * indicates significance at the 1, 5, 10 % level respectively.
The results are unchanged if we add conditioning variables.

Table A2: 1999 ITEs on food consumption: robustness checks

	With covariates			Without covariates		
	All data	Drop outliers	Drop percentiles	All data	Drop outliers	Drop percentiles
			Cross section			
ITE May	32.57	20.72	9.65	29.37	19.37	8.78
	[15.88]**	[10.19]**	[5.59]*	[14.61]**	[10.50]*	[5.71]
ITE Nov.	29.63	18.84	14.41	26.34	17.36	13.50
	[15.02]**	[9.42]**	[4.72]***	[13.79]*	[9.70]*	[4.93]***
			Cross section conditioning on pre-program expenditure			
ITE May	35.19	21.7	10.15	32.71	21.68	9.93
	[17.43]**	[11.01]**	[5.50]*	[15.59]**	[11.07]*	[5.57]*
ITE Nov.	30.42	18.46	13.36	28.04	18.18	13.11
	[16.27]*	[10.09]*	[4.47]***	[14.69]*	[10.14]*	[4.60]***
			Difference-in-difference			
ITE May	29.92	19.95	7.28	29.17	19.17	7.44
	[14.95]**	[11.48]*	[6.95]	[14.78]**	[11.23]*	[6.87]
ITE Nov.	27.26	18.35	11.97	26.15	17.17	12.17
	[14.20]*	[10.77]*	[6.48]*	[13.97]*	[10.44]	[6.32]*

Monthly pesos per adult equivalent at Nov. 1998 prices. Standard errors in brackets clustered at the village level.
***, **, * indicates significance at the 1, 5, 10 % level respectively.
The pre-program expenditure variable uses total weekly expenditure data;
the results are robust to using the sum of separate expenditure data on fruits and vegetables, grains and cereals, fish, meat and dairies, and industrial products. The "drop outliers" columns drop consumption levels bigger than 10000 pesos, while the "drop percentiles" columns drop the first and last percentile.
See Table 1 for a list of conditioning variables.

Table A3: Food prices used to compute difference-in-difference estimates of program effect on prices

Prices legend			
p1	tomatoes (kilo)	p19	chicken (kilo)
p2	onions (kilo)	p20	pork (kilo)
p3	potatoes (kilo)	p21	beef (kilo)
p4	carrots (kilo)	p22	goat (kilo)
p5	oranges (kilo)	p23	fish (kilo)
p6	bananas (kilo)	p24	biscuits (kilo)
p7	apples (kilo)	p25	beans (kilo)
p8	lemons (kilo)	p26	eggs (kilo)
p9	lettuce (unit)	p27	milk (liter)
p10	nixtamal masa (kilo)	p28	lard (kilo)
p11	corn grains (kilo)	p29	pastry (bag)
p12	Bread (unit)	p30	soft drink (bottle)
p13	Bread ``de caja'' (unit)	p31	Sardines (150 grs. in 98m, 400grs. after)
p14	wheat flour (kilo)	p32	Tuna can (175 grs.)
p15	soup (200 grs.)	p33	aguardiente (liter)
p16	rice (kilo)	p34	coffee (small pack)
p17	Tortillas (kilo)	p35	sugar (kilo)
p18	corn ``hojuelas'' (unit)	p36	vegetable oil (liter)

Table A4: Difference-in-differences estimates of the effect of Progresa on village prices

	p1	p2	p3	p4	p5	p6	p7	p8	p9
T	0.0826	-1.1782	-0.0435	-0.5462	0.1246	-0.0443	-0.0414	-1.3424	-1.6077
	[0.2582]	[0.4387]***	[0.2357]	[0.4391]	[0.2012]	[0.1677]	[0.3895]	[0.9675]	[1.2532]
T*98o	0.095	1.2498	0.0609	0.877	-0.5583	0.2174	-0.2832	1.8117	1.6452
	[0.3840]	[0.4985]**	[0.3974]	[0.6473]	[0.3953]	[0.2851]	[0.6732]	[1.0401]*	[1.2807]
T*99m	0.0804	0.781	-0.3818	0.1531	0.0866	-0.3466	-0.1483	1.1914	1.2465
	[0.7453]	[0.5417]	[0.3099]	[0.5599]	[0.2987]	[0.2831]	[0.7589]	[1.0111]	[1.2876]
T*99n	-0.8173	1.3505	-1.3779	1.5488	-1.6462	-1.1732	-0.325	3.2171	2.0641
	[0.3489]**	[0.8422]	[0.8913]	[2.5669]	[0.6641]**	[1.4749]	[0.5746]	[2.2543]	[1.3830]
Obs.	1034	990	948	369	678	698	426	548	413

	p10	p11	p12	p13	p14	p15	p16	p17	p18
T	-0.5039	0.0057	-0.3148	-1.69	0.0501	-0.3291	-0.1483	0.0265	0.8105
	[0.3412]	[0.2665]	[0.3250]	[1.3105]	[0.1785]	[0.4101]	[0.1409]	[0.1299]	[0.9233]
T*98o	0.4998	0.2034	0.3913	1.4979	-0.0945	0.2555	-0.1047	0.0531	0.1171
	[0.4262]	[0.3482]	[0.3511]	[1.3912]	[0.2497]	[0.4202]	[0.1859]	[0.1758]	[1.3075]
T*99m	0.2958	-0.428	0.0864	2.0122	-0.2671	0.264	0.1945	0.3573	0.694
	[0.4109]	[0.3291]	[0.6539]	[1.3717]	[0.3055]	[0.4162]	[0.2806]	[0.3769]	[1.5655]
T*99n	0.8789	2.5907	4.0232	0.4852	9.1043	-0.3298	-0.569	-0.4817	-1.6231
	[4.4228]	[1.7468]	[9.9232]	[1.4638]	[9.2109]	[0.5394]	[0.5809]	[0.4022]	[1.1575]
Obs.	365	640	750	390	678	1233	1375	424	565

	p19	p20	p21	p22	p23	p24	p25	p26	p27
T	-0.2255	-0.5765	-0.1634	-15.4505	-1.6939	-0.15	-0.3617	-0.9393	-0.34
	[0.6422]	[0.9607]	[1.2435]	[9.0361]*	[2.0772]	[0.2455]	[0.1621]**	[0.3405]***	[0.2410]
T*98o	-1.8291	-1.8317	-1.3589	13.7839	-6.8775	0.1938	0.0172	1.1282	0.3435
	[1.3035]	[1.6762]	[3.2008]	[11.1087]	[3.9947]*	[0.2641]	[0.3141]	[0.4336]***	[0.3052]
T*99m	-0.5113	0.9343	1.1377	12.0755	5.714	0.129	0.3623	0.5862	0.3434
	[0.8389]	[1.2960]	[1.7734]	[11.5156]	[5.6679]	[0.2637]	[0.2650]	[0.4429]	[0.4402]
T*99n	-1.2303	0.9294	-0.0991	15.3242	3.4506	0.1216	-0.2787	0.4151	-2.3614
	[2.2299]	[1.1187]	[1.2644]	[9.0350]*	[2.7004]	[0.4785]	[0.4876]	[0.7810]	[3.3976]
Obs.	486	566	313	334	344	1375	1194	1206	833

	p28	p29	p30	p31	p32	p33	p34	p35	p36
T	-0.0689	-0.1552	0.0916	-0.0645	-0.0312	-0.3793	-1.5319	-0.1483	-0.1349
	[0.3556]	[0.1894]	[0.2142]	[0.1266]	[0.0939]	[0.7805]	[0.5373]***	[0.0950]	[0.1196]
T*98o	-0.0634	0.1684	-0.151	0.1084	-0.0026	1.2379	2.2448	0.1084	0.1579
	[0.5199]	[0.2163]	[0.2647]	[0.1734]	[0.1331]	[1.1330]	[0.7657]***	[0.1324]	[0.1828]
T*99m	-0.3067	-0.068	-0.3152	0.542	0.2061	1.5668	0.3668	0.1521	0.1635
	[0.5517]	[0.3063]	[0.3013]	[0.2638]**	[0.1485]	[1.5627]	[0.7374]	[0.2031]	[0.1800]
T*99n	0.5788	0.6931	6.3978	-0.4729	-0.3143	0.3309	-0.0825	0.6451	2.5376
	[0.7721]	[0.9239]	[10.4329]	[0.5949]	[10.0995]	[0.8828]	[6.4283]	[0.7407]	[2.2574]
Obs.	634	488	922	1272	1021	757	636	1431	1219

Standard errors in brackets clustered at the village level.
***, **, * indicates significance at the 1, 5, 10 % level respectively.