Measuring Vulnerability:
Who Suffered in the 1995 Mexican Crisis?*

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Abstract: The paper identifies the demographic groups that suffered the largest income falls during the 1995 crisis in Mexico and which groups recovered most quickly. It uses quantile analysis to identify those suffering "catastrophic" falls in income and employs distributional weights to identify those most "vulnerable." The incidence and overall impact of common coping strategies-putting additional family members in the workforce- is also examined.

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1. Introduction

The Mexican crisis of 1995 led to massive falls in wages and household income of roughly 30% that have not yet been recovered five years later (see figure 1). This paper concerns itself with understanding who suffered disproportionately during the crisis, how families coped, and which families have recovered most quickly. It then attempts to identify who the most "vulnerable" are.

The analysis studies per capita income changes of families across the period 1994-1997 using the Mexican National Employment Survey (ENEU) which is structured as a rotating panel. It employs quantile analysis to characterize not only the families who suffered the median fall in income, but also those suffering the "catastrophic" falls at the lower tail of the distribution .

To our knowledge, this, along with Glewwe and Hall (1998) who identify the determinants of consumption variance in Peru during the 1985-1990 stabilization program, are the only studies to use panel data to analyze vulnerability.

2. What is Vulnerability

As the literature recognizes, (see, for instance, Glewwe and and Hall 1998) vulnerability is a question both of changes in economic status and the initial position in the income distribution. Even if well-fed people were to experience higher variability in income, we would not *necessarily* consider them more "vulnerable" than those with low caloric intake with lower variance. What is necessary to categorize a family as vulnerable is therefore some combination of both the probability of bad outcomes as well as some measure of their "badness" as given by a social welfare function. One possible map embraced by the World Bank implicitly gives a zero weight to the welfare of families above the poverty line and, in more sophisticated versions, weights distance below the poverty line (squared) as essentially the sole criterion for concern and social policy. This may lead to the identification of the vulnerable as those with a “high” probability of falling below the poverty line, or of falling further into poverty. [1]

This is an extreme mapping. It is not obvious that we shouldn’t care about the middle class workers who, upon becoming unemployed, may nonetheless have to take defensive measures that may have strong and persistent negative social affects, such as pulling children out of school. Further, in the same way that poverty lines are, to some degree constructs that recognize relative social position, it is also not clear that variability in itself shouldn’t receive some weight: perhaps a large fall by an upper middle class family should not be given a zero weighting while a small fall by a marginal poor family gets much higher weighting. Finally, the discreteness imposed by the poverty line adds additional complications. For instance, how do we weight 1% income fall of a family infinitesimally above the poverty line compared to that of family infinitesimally below?

For these reasons, we prefer a more continuous set of weights. One possibility is that suggested by Squire and van der Tak 1975. The utility function

$$U(c) = \frac{1}{(1-l)} c^{1-l} \quad \text{if} \quad l \neq 1$$

$$= \log(c) \text{ if } \; l = 1$$

has the property that its first derivative

$$U_c = c^{-l}$$

can capture different degrees of progressiveness by varying l: for $l = 0$, all changes in consumption “c” are weighted equally across the income spectrum, for $l = 1$ the weight rises with the inverse of the ratio of individual household consumption; for $l = 2$ the weight rises with the square of the ratio. Squire and van de Tak argue that for most

[1] We are indebted to Quentin Wodon for bringing this point to our attention.

governments the value l might center on 1. A value of 2 might bring us closer to the concept embraced by the squared poverty gap. If we normalize by marginal utility at the mean level of consumption, $\bar{c}$, we can define the weight (d) to be applied to an arbitrarily small change in the income of a family at point "c" in the distribution as:

$$d = \frac{U_c}{U_{\bar{c}}} = (\bar{c}/c)^{l} \, . \qquad (1)$$

3. Application to the Present Data:

We face multiple problems in implementing this strategy:

First, unlike Glewwe and Hall, the ENEU does not measure consumption, which theoretically is what "utility" depends on, only income. Unless we assume that income follows a random walk, or that households have no ability to smooth (no assets or access to credit markets of any kind) we cannot interpret observed changes in income as changes in actual consumption. On the other hand, it is unlikely that many agents were able to smooth what has turned out to be a relatively permanent shock to their household incomes. Thus, for the crisis period, perhaps we are not so far off the mark.

Second, the changes in income brought on by the 1994 recession were not infinitesimal. Average income fell around 30%. In theory, therefore, a more complex formula employing information on initial and final consumption levels is technically correct.[2] However, this approach seems unworkable in light of the extraordinary degree of income mobility the data suggest. Figure 2 presents the pattern of movement among those out of the labor force, those unemployed, and the five income quintiles of those reporting positive household incomes. It suggests that only 30% of households are in the same income quintile after 15 months and that 28% jump from the bottom to the top two quintiles. There are several possible explanations. First, there is a very high degree of

[2] See Squire and van de Tak p. 137

mobility in the labor force and frequent movements among formal and informal sector jobs implying rapid changes in reported income. Second, roughly 40% of household heads are self-employed and entrepreneurs experience much more volatile income flows than the salaried formal. Third, the recall by those interviewed is very poor.[3]

If we assume the noise is broadly symmetrical, however, we may generate a median fall in income in a particular group with a fair degree of confidence. But a critical problem for the application of the non-infinitesimal approach arises in locating a family's "permanent" income position in the overall distribution. As figure 2 suggests, a family in quintile 1 may actually be a well off family showing temporarily low income.

Though the ENEU is an excellent employment survey, it contains essentially no reliable data on measures of wealth that could help us measure permanent income. Instead, we generate a crude measure using the median income of the manzana, or city block or group of blocks, that comprise the neighborhood where the family lives. Since the larger cities that the ENEU draws from are likely to have high degrees of geographical stratification, these may be reasonable proxies. Using neighborhood income helps avoid the problem of income changes simply capturing reversion to the mean: an observed poor family has a higher probability not only of having lower human capital, but also of having "bad luck" that, if it not consistently unlucky, implies that its income growth will appear higher as income returns to "normal" levels.[4] The reverse is true for the well off and both effects will have the effect of overstating the average gains of poor people and understating those of the rich. In calculating the neighborhood income, we use all the data available in the cross sectional survey and then drop any manzanas that contains under 20 families in the survey to avoid temporary unemployment of one family unduly biasing manzana income.

[3] What is striking is that, as found by Arango and Maloney (1999) in Argentina, roughly 20% of those in the bottom quintile are found in the top two quintiles in the last period. This suggests either miraculous social mobility by the poor, or that many categorized as poor are, in fact, relatively well off families who, for whatever reason, show temporarily low incomes. This also suggest, as Maloney and Arango (2000) argue, that the common finding that unemployment especially effects the poor is a tautology – the unemployed show low temporary household incomes.

[4] We are grateful to Francisco Ferreira for bringing this point to our attention.

The bottom line is that the weighting schemes that make use of initial and final consumption (income) are not likely to be of great applicability here. With full cognizance of the limitations of the approach, we weight each observed change in income by the weights in equation 2 applied to the mean income of the decile of manzana income in which the household is found.

4. Data

The National Urban Employment Survey (ENEU) conducts extensive quarterly household interviews in the 16 major metropolitan areas for the period from 1992-1997 which includes the crisis. The sample is selected to be geographically and socio-economically representative. The statistical agency (INEGI)[5] expanded it significantly over the period by adding municipalities, however, we include only those municipalities present in every year of the survey to prevent changes in sample composition. The questionnaire is extensive in its coverage of participation in the labor market, wages, hours worked, etc. that are traditionally found in such employment surveys. INEGI's treatment of sample design, collection, and data cleaning is careful. Surveys and documentation of methodology are available on request.

The ENEU is structured to track a fifth of each sample across a five quarter period. To construct the panels, workers were matched by position in an identified household, level of education, age and sex to ensure against generating spurious transitions. Using just the first variables to concatenate and following changes in sex across the panel led to mismatching (or mis-reporting) of under 0.5 percent.

[5] Instituto Nacional de Estadistica, Geografia y Informacion.

5. Quantile Analysis: Measuring Median and Catastrophic Shocks

Conditional mean regression estimators, such as Ordinary Least Squares, are traditionally used to estimate linear relations among variables. Minimizing the squared sum of errors allows estimating the values of the parameters that predict the mean of the dependent variable, conditional on a set of explanatory variables chosen. However, if the sample is not completely homogeneous, such techniques may hide differential effects of the regressors across the distribution that may be a critical part of the story being told. Further, if there are large outliers, or the distribution of the disturbances is non-normal, conditional mean estimators may be inefficient and often biased.

These concerns can be reduced somewhat by estimating the conditional median regression where half the errors lie above, and half below the fitted curve. Quantile analysis, introduced in Koenker and Bassett (1978), extends this analysis to estimating curves where approximately ϑ% of the errors will be negative and (100-ϑ)% of the errors will be positive.[6] If the errors are i.i.d., slicing the distribution at different quantile levels has little effect on parameter estimates and little information is lost in a single measure of the conditional central tendency, such as the parameters generated by OLS or median regression. However, figure 3 shows that asymmetries or heteroskedasticity in the distribution of errors may lead to substantially different estimates of the impact of the variables under study.

Quantile Analysis may be particularly appropriate to the present application for three reasons. First, by construction, the percentage change variable is unlikely to be Gaussian in distribution since it is bounded below at –1 and may have very long right tails. Second, studying vulnerability, we are particularly interested in what happens at the lower tail of the distribution. It may be that there are no differences in median income changes by demographic group. However, one group may suffer disproportionate “catastrophic” shocks- those at the very low end of the distribution- which are of special interest.

[6] The technique has generally been applied to estimating returns to education, (Buchinsky 1994).

Third, differences in employment patterns among social classes may lead to biases in estimates of overall impact of crises. This is revealed clearly in figure 4 which plots percentage change income against the log of the mean neighborhood income. What is readily apparent is that the lower middle group shows far more extreme "upside" movements in income than the higher income groups. Several factors may be responsible for this. First, there may be more turnover among workers with lower human capital and hence less job attachment. The probability that the chief breadwinner will suddenly get a job and tripling or quadruple family income may be higher for poor families than for the better off. Second, the probability of being self-employed also decreases with income. Since self-employment, as any small business, shows much greater income volatility than the formal salaried employment, this may also lead to a higher concentration of extreme positive values. [7] It will also lead to more negative values, but these are bounded at –1 and hence may not offset the upward bias to income gains among the less well off. Looking at the lower quantiles that capture only negative shocks reduces this effect.

In all the empirical work below, we present results of the quantile analysis at ϑ= 50 (the conditional median regression), ϑ= 20 where 20% of the deviations lie below the estimated regression, and ϑ= 80 where 80% lie below. We regress the percentage change in household income on a set of dummy variables. These dummies capture family characteristics that include human capital variables (age, schooling) of the household heads, household structure (single mothers, households headed by married couples with children, number of children etc.), labor market sector variables (formal salaried, informal salaried, informal self-employed), and whether the father became unemployed.[8] Conditioning on all these variables at once allows disentangling whether, for instance, informal groups are particularly vulnerable, or whether it is just that poorly educated people, which the informal are disproportionately, who are vulnerable. In the final

[7] See Maloney (1999a, 199b), Levenson and Maloney (1998)

[8] We use the term 'informal' here to refer to those unprotected by labor law, more specifically, owners of firms fewer than 16 employees who do not have social security or medical benefits. In fact, under 1% of these firm have more than 5 employees so the definition corresponds closely to that commonly used in the development literature. Formal salaried workers are defined as those in firms of over 16 workers who enjoy labor protections.

specification, we include dummies to capture frequently cited coping strategies-whether or not to put a wife (or other adult) or child in the labor force.

The regressions can be seen as capturing whether there are differences in the distribution of shocks that each demographic group faces. For instance, if male headed, two parent households are the base category, and the dummy for female headed families at the median shows a significant –5%, this suggests that "on average" female headed families were hit 5% worse. If the coefficient is the same at the 20^{th} and 80^{th} quantiles, then across the distribution, female headed families did consistently worse by the same amount. However, if at the 20^{th} quantile, the coefficient on the female dummy were -0.10, this would suggest that not only did women overall get hit worse on average, but among those who really took severe hits, female headed households took even more severe hits. Thus, quantile analysis can offer a richer description of the impact of the crisis both by capturing median differences in income falls, but also by revealing differences in exposure to catastrophic shocks.

6. Results

Broad trends by income quintile

Table 1 presents the results of regressing the percentage change in income across the five periods on the four "permanent" household income dummies using as the base category those with the highest incomes. The constant suggests a dramatic fall of 26% in the income of this group and there are no significant differences with other income groups. Among those who experienced very high positive shocks, the bottom quintile did roughly 8% better than the top quintile and among those experiencing truly catastrophic shocks the bottom two quintiles seem to have suffered roughly 4% less. Though this is small comfort, it is not the case that poor households suffered larger income falls.

Impact by household characteristics

Table 2 tabulates the results of the regressions on household characteristics during the crisis for 8=0 and 8=2. We include four dummies for education level of the head –primary incomplete, primary complete, secondary incomplete, secondary complete with the base category being those with college. It also includes 2 age dummies, one for those under 25 and one for those over 45. There is a dummy if there are more than the mean number of children (2.4) and 3 dummies for household structure: single mothers with children, single women without children, and single men without children. There are also three dummies for the sector in which the household head works: informal self-employed, informal salaried, and out of the labor force. The constant captures the base category of families headed by college educated males of age 26-45 working in the formal sector, with less than the mean number of children.

We include no dummy for whether the head became unemployed since we are interested in total income shock, whether through real wage falls or through loss of job. Further, we include no household coping variables so the income differences should be seen as the total effect, after households have taken all coping measures.

The median unwieghted regression suggest that those with only some amount of primary education suffer an income fall roughly 4% less than the base group. Household structure seems largely irrelevant to the outcome. The only occupational group that suffered disproportionately are the self-employed. This is not surprising as self-employed incomes show far more variance across the business cycle than formal salaried labor.[9] This should probably not be taken as sufficient evidence of the sector serving as a safety net, or as being particularly precarious since these fluctuations also correspond to pro-cyclical movements in sector size in the 1987-1993 period. Informal salaried workers appear not to suffer disproportionately at the median.

[9] Maloney (1998), Maloney and Wodon (2000) find that self-employed show higher variance in incomes more generally. This is consistent with the mainstream literature on firm dynamics (see Levenson and Maloney 1998).

The results change somewhat for those suffering catastrophic shocks (20th quantile). Again, primary educated workers appear to suffer less, but the coefficient on older workers now suggests a significant 3.5% fall relative to middle age workers and almost 9% relative to the young. Somewhat surprisingly, single men are the only group who suffer a significant fall (6%) relative to the base group. The self-employed suffer greater shocks than the formally employed, but again, the informal salaried are not particularly more affected. Households headed by those out of the labor force do seem to suffer very significant shocks that did not appear at the median.

At the 80th quantile, primary educated workers seem to have enjoyed fewer large positive shocks than the base category. Combined with the evidence from the 50th and 20th quantiles, this would suggest that the variance of these workers is simply less than for those more educated. Those with more children did slightly better as did single mothers, while single women without children enjoyed smaller positive shocks. Again, consistent with an overall higher variance, the self-employed experienced substantially greater positive shocks (13%). Somewhat surprisingly, the informal salaried and those out of the labor force did also.

Vulnerability: Changes in Utility

The last columns of table 2 present the results for $l = 2$, the extremely progressive weighting. Predictably, the results for $l = 1$ lie between the extremes and are not reported (available on request). Not surprisingly, at the median, the education and age variables, which are correlated with permanent income, have reversed sign and "vulnerability" appears to increase with lower education. However, the household structure variables remain robustly non-significant with the exception of single mothers who now appear less vulnerable than before. The self-employment dummy falls in value and significance suggesting that this group is not among the poorest while the reverse is true for the salaried informal. Both these conclusions are somewhat suspect, however, since wage differentials (and hence the weights) obscure true differences in utility due to job quality (independence, benefits) and payment in kind (30% of informal salaried are related to the firm owner).

At the 20th quantile, the same human capital effect appears with younger and less educated workers appearing more vulnerable. Families with larger than average families now appear to have a negative and significant effect, but again, among the household structure variables, only being single mother is significant and again positive. The informal and OLF dummies again suggest greater negative hits by these groups, but at the 80th quantile, these, as well as those with larger families, also show greater positive shocks.

7. Coping strategies

Table 2 also adds the set of "coping" dummies for whether the head, another adult (spouse) or children enter the labor force. Conditioning on these variables means the coefficient on income changes by group should be interpreted as the "partial," or "impact" effect, that is to say, before any coping occurs.

The median regression suggests that putting any member of the family in the market largely offset the median fall by raising houshold incomes by roughly 25%. But looking at the difference between the "demographic" regressions and those with coping strategies reveals several striking results.

First, the overall effect on the "impact" coefficients is not large. While the gain from putting an individual in the workforce is large, this does not seem to benefit any particular sub-group to large degree. Second, to the degree that the coefficient on any of the demographic variables changes, the effect is concentrated among those with less education. At the median, it is clear that the 4% premium that household heads with incomplete primary enjoy in the demographic regressions is due to their ability to put additional workers in the labor market. This is probably also the case with families headed by older workers who may have either working age children or a spouse unencumbered by child rearing responsibilities. Of some interest, the coefficient on single mothers become significant at the 10% level which may reflect that, of all groups they are the least able to employ these strategies.

At the lower quantile, the impact of coping strategies is roughly the same with the exception that putting a spouse in the market generates about 4 percentage points less offsetting increase in income. Among those who did best during the crisis, adding additional workers had substantially larger effects with spouses' entry yielding almost double the impact at the median and 2.5 times at the lower quantile. At every quantile, the partial effect for informal workers falls suggesting that these groups may also have greater flexibility in adding new workers.

The utility adjusted regressions suggest that these effects are larger among poorer workers.

What remains striking is the very limited impact that coping strategies have overall. Table 3 tabulates the percentage of households who put additional workers in the labor force, either spouses, children or themselves, as well as mean hours worked. As might be expected, the added worker effect becomes smaller with the neighborhood income of the family. But the numbers are never large. Further, in comparison with the "recovery" what is unexpected is that the substitution effect appears to dominate every category of added worker- families either cannot, or, persuaded by low wages do not put additional workers in the labor force. In the aggregate, this is probably a good thing. Virtually all serious studies of labor demand find own wage elasticities of under unity, generally under 0.5. This implies that a 1% increase in the size of the working labor force would lead to a 2% fall in wages or a net *decrease* in income to workers as a group. As a coping strategy for the poor, adding workers is self-defeating.

The stark bottom line is that most households do not have coping strategies that cushion the blow of an economic crisis by increasing income.   Upon reflection, this is should not be a surprise. The poverty headcount jumps dramatically during the crisis from 14.6 in 1994 to 20.5 in 1996. [10] If the majority of families have effective income coping strategies, this would not be the case.

8. Who Recovered Most Quickly

The right side of table 1 and all of table 4 repeats the exercise but using stacked panels available after the period where the crisis “bottomed out.” Preliminary analysis suggests that the period in which income of every quintile either grew or stayed the same was 1996:2 and this is the first period we include. The estimates give us the average 15 month growth rate in household income, again , by the same categories and quantiles as above.

What again appears in table 1 is that, in terms of raw income changes, the poor recovered faster than the wealthy at all quantiles. This carries over to table 4 which, again, suggests that families headed by less educated workers recovered more quickly. Those with completed primary education enjoyed income growth per 15 month period of 5.5% more than the wealthier groups who experienced no net income growth. Older workers, however, do significantly worse, experiencing a continuing 15 month income fall of 2% across the recovery period. Single mothers, who felt less of a fall initially, also appear to recover faster. However, single women seem to continue in crisis, falling an additional 4% per 15 month period.

The self-employed do as well as salaried workers which suggests that they do not recover their disproportionate losses. The informal salaried, however, experience growth rates of 3.2% above the formal salaried, despite the fact that they did not fall particularly farther. These results are largely replicated at the 20th quantile. At the 80th, the poorly educated again do relatively better, single women also do less well, and the informal sector again does disproportionately better.

[10] Wodon (2000)

The utility adjusted estimates present virtually an identical picture at the median, confirming the results from table 1 that that the gains are distributed heavily among the poorer elements. At the lower quantile, the negative coefficients on single women and older worker headed households are no longer significant suggesting that these groups, while experiencing more catastrophic income shocks, tend to be richer and hence less vulnerable. Single mothers now have a significantly positive coefficient.

Adding the coping variables suggests, unsurprisingly, that the benefits to household incomes of adding additional workers during upturns is half again as much as during the depressed downturns. This would be consistent with Cunningham's (1999) CITE findings that the added worker effect is lower during the crisis than in 'normal" times. If the expected gain in family income is lower, we should expect to find lower entrance rates.

9. Conclusion:

The paper attempts to identify which demographic groups suffered most during the 1995 crisis in Mexico and which groups recovered most quickly. It uses quantile analysis to identify those suffering "catastrophic" falls in income and employs distributional weights to identify those most "vulnerable." The incidence and overall impact of common coping strategies-putting additional family members in the workforce, is also examined.

The data suggest that the least educated and poor suffered slightly less during the crisis, but only due to having put other members of the household in the labor market. While the impact of coping strategies is large on the individual family, they do not seem to be able to mitigate the fall in income experienced by the vast majority. Overall, families cannot defend against large shocks to income. Further, when distributive weights are used to capture position in the income distribution, the less educated do show disproportionate losses in weighted utility and hence, are more vulnerable. As Glewwe and Hall found, several groups commonly thought to suffer disproportionately, in particular, single mothers, do not. Nor do the informal salaried experience disproportionate income falls. The least educated and poor are also among the most quick to recuperate their income losses in the recovery period. Informal salaried workers do disproportionately well although informal self-employed workers do not recover their exceptional losses.

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Figure 1: Mexico: Median Hourly Urban Wages

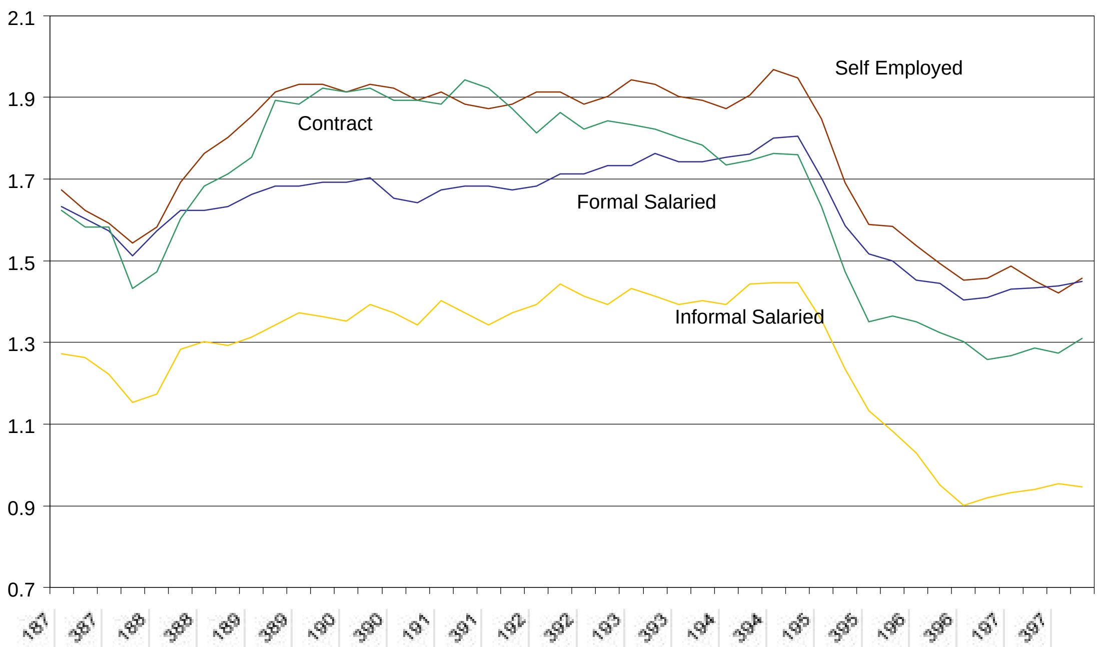


Figure 2: Household Income Transitions
Per Capita Household Income and Status of Household Head

Initial Quintile	Final Quintile							
	1st Q.	2nd Q.	3th Q.	4th Q.	5th Q.	Unem.	OLF	
1st Quintile	30	22	15	14	14	1	4	100
2nd Quintile	15	45	24	10	3	1	2	100
3th Quintiile	9	24	34	23	6	1	2	100
4th Quintile	6	10	23	37	21	1	3	100
5th Quintile	8	4	7	21	57	1	2	100
Unemployed	7	10	16	10	3	19	34	100
Out of Labor Force	6	3	3	3	3	5	76	100
Final Distribution	11	19	19	20	19	2	10	100

Notes: Each panel composed by individuals followed for five quarters.
Shading = probability of remaining in same sector. Boxed Cells Represent Positive Income.

Figure 3: Quantile Regression

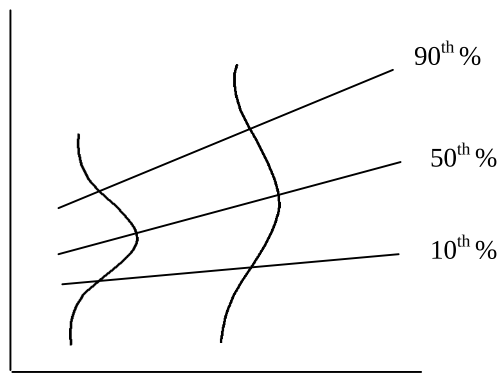
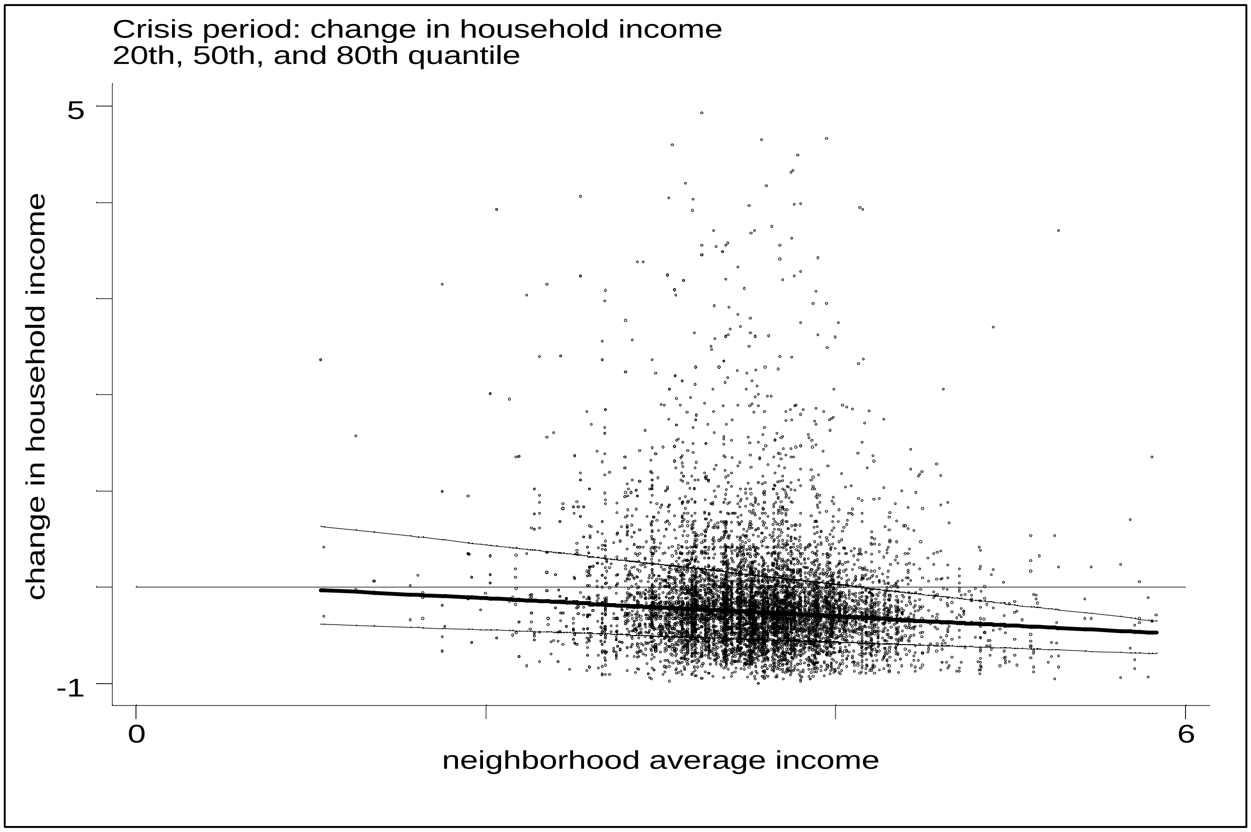


Figure 4: Income Changes and Neighborhood Income



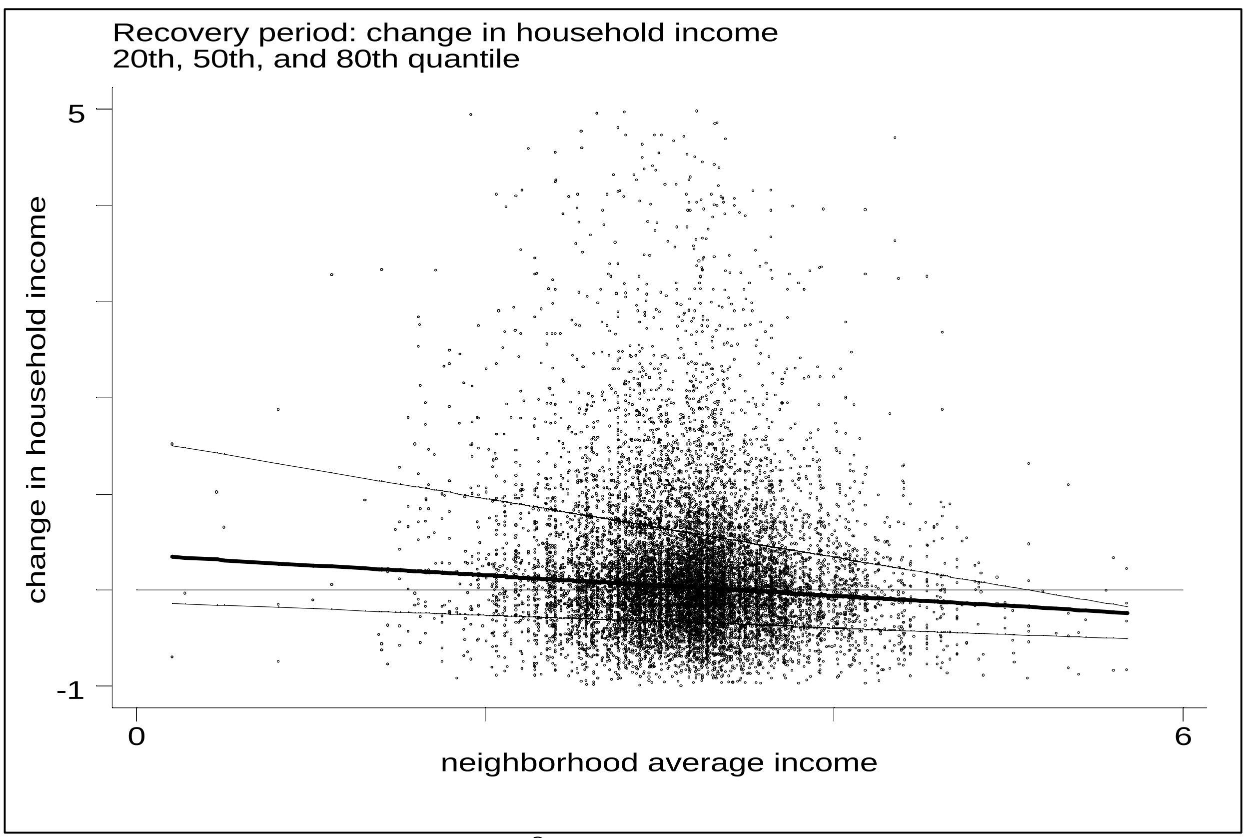


Table 1: Income Change by Income Quintile

	Crisis						Recovery					
	0.2		0.5		0.8		0.2		0.5		0.8	
	a		b		c		d		e		f	
Quintile 1	0.033	*	0.007		0.085	**	0.091	**	0.091	**	0.281	**
Quintile 2	0.048	**	0.016		0.006		0.053	**	0.046	**	0.112	**
Quintile 3	0.018		-0.0068		-0.0291		0.064	**	0.034	**	0.094	**
Quintile 4	0.011		-0.021		0.006		0.027		0.012		0.032	
_cons	-0.562	**	-0.260	**	0.115	**	-0.382	**	-0.004		0.508	**

Table 2: Income Change by Demographic Group and Coping Strategies
Crisis Period

	Unweighted						Weighted 1=2					
	Demographic			+ Coping Strategies			Demographic			+ Coping Strategies		
	0.2	0.5	0.8	0.2	0.5	0.8	0.2	0.5	0.8	0.2	0.5	0.8
	a	b	c	d	e	f	j	h	i	J	k	l
Primary Inc.	0.061 **	0.040 **	-0.058 **	0.049 **	0.010	-0.101 **	-0.355 **	-0.094 **	-0.011	-0.345 **	-0.129 **	-0.052
Primary	0.038 **	0.030 *	-0.054 *	0.040 **	0.004	-0.086 **	-0.326 **	-0.091 **	-0.008	-0.317 **	-0.127 **	-0.040
Secondary Inc.	0.012	0.006	-0.011	0.010	-0.002	-0.053 *	-0.251 **	-0.065 **	0.011	-0.235 **	-0.072 **	-0.015
Secondary	0.017	0.025	0.034	0.019	0.018	-0.016	-0.221 **	-0.033	0.049	-0.216 **	-0.036	0.015
Young	0.051 **	0.000	-0.044	0.074 **	0.006	-0.034	-0.167 **	-0.061 **	-0.030	-0.135 **	-0.056 **	-0.027
Old	-0.036 **	-0.018	0.023	-0.034 **	-0.025 **	-0.003	0.009	0.000	0.013	-0.021	-0.015	-0.009
> 2.5 Children	0.023 *	0.007	0.050 **	0.017	-0.005	0.008	-0.125 **	-0.016	0.078 **	-0.155 **	-0.033 **	0.030
Single Mothers	0.031	0.018	0.077 **	0.014	0.036 *	0.053	0.129 **	0.048 **	0.081 *	0.075	0.045 *	0.083 **
Single Women	-0.029	-0.019	-0.079 **	0.007	0.022	-0.015	-0.056	-0.014	-0.078 *	-0.020	0.008	-0.021
Single Men	-0.063 **	-0.026	-0.021	-0.046 *	0.000	0.024	0.007	0.005	-0.002	0.025	0.022	0.038
Self-Employed	-0.124 **	-0.066 **	0.134 **	-0.127 **	-0.071 **	0.091 **	-0.173 **	-0.044 **	0.164 **	-0.160 **	-0.051 **	0.108 **
Informal Salaried	-0.026	-0.015	0.056 *	-0.049 **	-0.015	0.014	-0.311 **	-0.077 **	0.060	-0.302 **	-0.086 **	0.021
Out of Labor Force	-0.105 **	0.008	0.174 **	-0.192 **	-0.055 **	0.073 **	-0.129 **	0.029	0.235 **	-0.162 **	-0.027	0.096 **
Constant	-0.520 **	-0.265 **	0.080 **	-0.537 **	-0.269 **	0.084 **	-0.346 **	-0.146 **	0.039	-0.376 **	-0.149 **	0.025
Head gets Job				0.269 **	0.269 **	0.310 **				0.160 *	0.210 **	0.742 **
Spouse gets Job				0.190 **	0.240 **	0.473 **				0.279 **	0.238 **	0.681 **
Child gets Job				0.254 **	0.269 **	0.416 **				0.498 **	0.308 **	0.609 **

Table 3: Income Change by Demographic Group and Coping Strategies
Recovery Period

	Unweighted						Weighted l=2					
	Demographic			+ Coping Strategies			Demographic			+ Coping Strategies		
	0.2	0.5	0.8	0.2	0.5	0.8	0.2	0.5	0.8	0.2	0.5	0.8
	a	b	c	d	e	f	g	h	i	j	k	l
Primary Inc.	0.094 **	0.033 **	0.050	0.087 **	0.025	-0.056 *	-0.161 **	0.035 **	0.411 **	-0.159 **	0.018	0.225 **
Primary	0.069 **	0.055 **	0.084 **	0.069 **	0.037 **	0.024	-0.122 **	0.053 **	0.482 **	-0.119 **	0.027 **	0.296 **
Secondary Inc.	0.046 **	0.035 **	0.033	0.048 **	0.029 *	0.000	-0.100 **	0.032 **	0.226 **	-0.095 **	0.017	0.176 **
Secondary	0.037	0.013	0.007	0.041 *	0.020	-0.022	-0.037	0.010	0.058	-0.046	0.010	0.052
Young	0.016	-0.013	-0.070	0.018	-0.003	-0.009	-0.009	-0.008	-0.042	-0.006	-0.005	-0.003
Old	-0.053 **	-0.021 *	-0.016	-0.070 **	-0.051 **	-0.018	-0.005	-0.022 **	-0.115 **	-0.037 *	-0.035 **	-0.071 *
> 2.5 Children	0.036 **	0.003	-0.001	0.006	-0.008	-0.024	-0.004	0.007	0.095 **	-0.045 **	-0.003	0.077 **
Single Mothers	0.032	0.035 *	-0.007	0.026	0.041 *	0.035	0.079 **	0.033 *	0.062	0.035	0.019	0.105
Single Women	-0.073 **	-0.041 **	-0.091 **	-0.052 **	0.005	0.042	-0.004	-0.033 **	-0.104	0.030	0.008	0.040
Single Men	0.020	0.009	-0.008	0.035	0.051 **	0.063	0.044	0.005	-0.085	0.071 **	0.037 **	0.054
Self-Employed	-0.135 **	-0.015	0.247 **	-0.143 **	-0.025 **	0.245 **	-0.151 **	-0.013	0.313 **	-0.155 **	-0.025 **	0.267 **
Informal Salaried	-0.025	0.032 **	0.194 **	-0.031	0.026	0.110 **	-0.192 **	0.036 **	0.541 **	-0.181 **	0.036 **	0.466 **
Out of Labor Force	-0.126 **	0.036 **	0.311 **	-0.169 **	-0.021	0.106 **	-0.148 **	0.037 **	0.321 **	-0.171 **	-0.013	0.110 *
Constant	-0.336 **	0.002	0.460 **	-0.345 **	-0.022	0.398 **	-0.203 **	-0.001	0.373 **	-0.224 **	-0.016	0.248 **
Head gets Job				0.285 **	0.382 **	0.820 **				0.321 **	0.369 **	1.566 **
Spouse gets Job				0.272 **	0.409 **	0.746 **				0.317 **	0.424 **	1.429 **
Child gets Job				0.306 **	0.385 **	0.574 **				0.421 **	0.568 **	1.488 **

Table 4: Coping Strategies

Neighborhood Quintile	% Families Adding Workers			Change in Hours Worked
	Head	Spouse	Child	
Crisis				
1	4.5	13.1	3.8	-1.4
2	3.9	11.3	4.4	-1.4
3	3.4	10.5	4.1	-0.8
4	3.0	10.6	2.3	-0.6
5	2.3	9.3	2.6	-0.6
Recovery				
1	4.3	14.3	5.7	-0.4
2	3.5	12.3	4.7	-0.1
3	3.5	11.8	3.5	-0.2
4	3.2	11.2	2.9	-0.4
5	2.9	9.1	1.9	-0.1