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Endogenous Persistent Shocks and Poverty Traps*

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Abstract

Adverse shocks are common in developing countries. Since markets are incomplete, households must significantly distort their decisions to cope with these shocks. These distortions not only affect current utility but can also increase the vulnerability to future shocks, which in turn could trap households in a low-income equilibrium. This paper uses Colombian longitudinal data to estimate the persistence of adverse shocks, which is found to be between 8 and 11 percentage points, and find that such persistence is mostly explained by decreases in consumption after a realized adverse shock. We also show that, while households in the lowest and highest quintiles use assets to smooth consumption, households in the middle of the wealth distribution decrease consumption significantly after a shock. We then propose a model and calibrate it with the persistence estimates to rationalize the observed behavior, and find that a poverty trap exists for the first two quintiles.

Keywords: Poverty traps, Persistence, Endogenous shocks, Welfare
JEL codes: D14, D91, I31

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1 Introduction

Adverse shocks are common in developing economies.[1] Since markets are incomplete, these shocks can significantly distort household decisions to smooth consumption. The magnitude and consequences of these distortions depend on households' socioeconomic status and the instruments at their disposal. A major concern about the reaction to adverse shocks is that households with limited instruments may follow strategies that increase their future vulnerability. In turn, an increase in the probability of facing a new adverse shock could perpetuate the use of harmful strategies, trapping households in a low-income equilibrium.

The purpose of this paper is to characterize such distortions as a reaction to adverse economic shocks, examine whether these reactions lead to an increase of their vulnerability to future shocks, and identify if they are consistent with a poverty trap. The paper thus falls in line with a long tradition in development economics studying the possibility of poverty traps. The evidence on their existence has remained remarkably elusive partly because most of the literature has focused on estimating asset accumulation equations in search of sufficiently strong nonconvexities (Kraay and McKenzie (2014); McKay and Perge (2013)). As emphasized in Barrett and Carter (2013), this conventional test of poverty traps faces formidable identification challenges. This motivates their search for alternative approaches, like identifying behavioral responses and specific mechanisms that only make sense under the existence of potential poverty traps. Our study follows this strategy.

We build on the idea that households may pursue a number of dynamically harmful strategies following an adverse shock. Decreasing food expenditure could cause malnutrition, in turn affecting long-term physical and cognitive development, educational attainment, and productivity in general (Alderman, Behrman, and Hoddinott (2005); Strauss and Thomas (1998)). Decreasing education expenditure could decrease human capital accumulation, either via a change to a lower quality institution or retiring from it. This in turn decreases productivity, the probability of employment or the probability of a high-income job. A change of location can also have disastrous effects in terms of vulnerability. Moving to a lower quality dwelling could increase the risk of becoming ill. Moving in with relatives can also generate crowding, which could increase the probability of adverse health shocks.[2]

[1] For example, according to the Colombian Longitudinal Survey (ELCA) of 2010, more than 30% of urban households in Colombia reported an adverse shock in the previous year.

[2] The previous strategies could be grouped as strategies that decrease household expenditure. Other strategies, such as working more hours or having more members of the household working, rely on increasing household's income. These can also generate future vulnerability, for example in terms of health and labor shocks. Working extra hours could lead to stress and exhaustion, while new jobs could be low quality or

Identifying the effects of the strategies adopted following adverse shocks is important to formulate welfare-increasing policies. Moreover, the use of dynamically harmful strategies is presumably more prevalent in poor households that usually do not have access to formal credit markets, or are already indebted and cannot borrow more. Thus, identifying how strategies depend on households' characteristics is key to target such policies to the most dynamically vulnerable households and avoid potential poverty traps.

We first use Colombia's unique Household Panel Survey, ELCA, to measure the persistence of adverse shocks and how such persistence depends on consumption decisions. The ELCA completed its first follow-up in 2013, following the baseline measure in 2010. We can thus use these two time periods to test for the presence of our purported dynamic mechanisms. We find that adverse shocks are quite persistent, and that such persistence is higher for households that decreased consumption as a strategy to cope with the adverse shock. We also characterize such consumption decisions and find that households in the fourth quintile of the wealth distribution decrease consumption significantly after being hit by an adverse shock, while maintaining their level of assets. In contrast, households in the bottom and top of the wealth distribution behave as the standard literature suggests, i.e. they decrease their asset levels to smooth consumption.

We then propose a model that rationalizes the observed consumption decisions and incorporate the previous estimates. In the model, a household maximizes utility but is subject to random shocks over time. The shocks are persistent and depend on the level of consumption. The household only has at its disposal a riskless asset to smooth consumption that has an exogenous debt limit as in Huggett (1993). We show how poverty traps can arise when the probability of facing an adverse shock exhibits a nonconvexity that increases such probability significantly when consumption falls below a threshold.

The intuition behind our results is twofold. First, sufficiently rich households will try to maintain their consumption above the vulnerability threshold by sacrificing assets at a higher rate. However, at some point this strategy becomes too costly to follow because the household still needs assets in the future to smooth consumption in case an adverse shock arises. At this level the household decides to decrease its consumption significantly below the threshold to protect its assets since a small decrease in consumption will have similar dynamic effects on its vulnerability, a consequence of the nonconvexity assumption on the probability. This behavior is consistent with the one found for the fourth quintile in the empirical section.

transitory. However we will not focus on these strategies given the available data.

Second, poorer households with low consumption and initial debt that do not experience adverse shocks are able to repay their debt slowly. When they pay their debt completely, they will incur in new debt to increase their consumption above the threshold that defined their higher vulnerability. The optimal response for these households generate a poverty trap that impedes their accumulation of asset holdings. Combining these theoretical results with the empirical estimates, we find that urban Colombian households in the first two quintiles are currently trapped in poverty. Moreover, households in the first quintile that experience an adverse shock have large welfare losses when compared to households that do not. Such losses are higher than the ones found in papers with completely exogenous shocks.

The organization of the paper is as follows. The next section explores how persistent and endogenous are adverse shocks, and how households react in terms of consumption and asset hondings when they are hit by an adverse shock using the ELCA. The third section proposes a model that is calibrated with the estimates from the previous section, and rationalizes the reactions observed in the data. The last section concludes.

2 Empirical patterns among Colombian urban households

In this section we take advantage of the Colombian Longitudinal Survey (*Encuesta Longitudinal Colombiana*, ELCA) to explore some empirical patterns in the reactions of households to adverse shocks. We focus on the following set of patterns that are consistent with our theoretical framework. First, households facing adverse shocks in the past are more likely to face adverse shocks in the future than other (comparable) households not stricken with bad luck. Second, most households react to adverse shocks by reducing net assets to maintain their consumption, yet households in the middle of the wealth distribution appear to sacrifice consumption and not reduce their asset holdings. Third, these different strategies have real consequences. In particular, we demonstrate that households not reducing food consumption (relative to their expected level absent bad shocks) face lower persistence of bad shocks. We briefly present our data initially, and next discuss each of these three pieces of evidence.

2.1 Data

The ELCA (Bernal et al., 2012) is the first nationally representative household panel survey in Colombia. We focus on data on urban households,[3] as all the rural households facing a

[3] We also explored the rural component of the survey. However, all the households appear to have the same reactions to adverse shocks. We interpret this as evidence suggesting that most of the rural households in the survey are within a poverty trap. This view is also suported by official statistics that estimated the

poverty trapas and the most important variable in our analysis is the incidence of adverse shocks. The survey started in 2010 and the first follow-up was in 2013.

In 2010, the “adverse shock” question inquired whether, within the past 12 months, households experienced any of a rich set of adverse events, including illness, job loss, abandonment of key members of the household, bankruptcies, loss of remittances, fires, etc. The full list of events, together with a detailed description of each of our variables is in Appendix Table A-1. On average, Table 1 shows that about a third of households were hit by adverse shocks, and this does not seem to be strongly correlated with wealth (we partition the sample between those above and below a simple wealth index for description).

In 2013, a similar question was asked again. The most important change for our purposes is that households self-declared the importance of shocks for their stability: low, intermediate or high. We focus on the latter two, as they are not just the ones likely to be significant adverse shocks, but because there is further information on the month and year of the shock, so we can construct binary variables for the incidence of shocks within the entire period or in specific years within the period. Around 49% of households were hit in this period, which was both longer and marked by important weather shocks known as the winter wave (*ola invernal*). Households below median wealth were affected at a higher rate (54%) than those above median wealth (45%). When breaking this by year of occurrence, 16% of households (15% among the relatively rich, 17% among the relatively poor) faced shocks in 2011, whereas the corresponding figure for 2012 was 25% (22% among the wealthier, 27% among the poorer).

We also take advantage of information on reported food consumption (per person) in our analysis to explore whether households sacrifice basic consumption and, if so, if this seems to affect the persistence of shocks. This is also described in Table 1, revealing an average expenditure per month of about 97,323 Colombian pesos per person in the full sample (close to 30 US dollars), and a figure about 23% larger among the relatively wealthier households and 23% smaller among those below median wealth. Net assets are 889,859 Colombian pesos on average for all households, more than twice as large for households above median wealth, and a negative (debt) position of 127 thousand pesos for households below median wealth.

Other key variables in our analysis are a rich set of controls for household and dwelling characteristics listed in Appendix Table A-1 and described in Appendix Table A-2. The breakup of shocks by the set of most important types and their timing is showing in Appendix

poverty rate to be around 50% of rural households for these years, in contrast to less than a third of the households in urban areas.

Table A-3.

2.2 Persistence of bad shocks

A key idea of our theoretical framework discussed below is that households once stricken with bad shocks may endogenously face future shocks with higher probability, as a result of the choices they make to face these adverse circumstances.

We therefore start by documenting that households once affected by adverse events are more likely to be affected a second time, relative to comparable households not stricken with bad luck. Of course the key challenge here is to find "comparable" households. The most naive approach, yet useful as a benchmark, is to compare among all set of households the incidence of shocks between the two waves of the ELCA (that is, experiencing shocks some time between 2010 and 2013) as a function of having experienced any adverse shock prior to 2010. Clearly, a positive coefficient on previous shocks can hardly be interpreted causally in such approach, most notably because of selection bias. Households affected with negative shocks in the past may have a number of additional characteristics affecting their vulnerability to adverse circumstances, thus making them more prone to select into the group of affected households in the future as well.

Absent an instrument or natural experiment that randomly assigns exposure to initial adverse shocks, one way to deal with this problem is to control for relevant predetermined household characteristics that may influence shock exposure. Of course, this relies on the relatively strong assumption that controlling for observables is sufficient to eliminate the selection bias. However, a comparison of the simple ordinary least squares regression with and without controls may be revealing of the apparent quantitative importance of controlling for observables.

Columns 1 and 2 of Panel A in Table 2 perform these initial exercises. To increase the comparability of households as well as the number of variables that we can treat as predetermined and use as controls, we narrow our attention to households living in the same dwelling for the past two years prior to 2010. Column 1 shows that households experiencing an adverse shock before 2010 are 12 percentage points more likely to face one again between 2010 and 2013, from a a baseline average incidence of adverse shocks of 44% over this period (with a standard deviation of 0.50). Thus, this correlation is quantitatively large: close to one-fourth of the mean and of the standard deviation. In this column, as in all regressions that we present below, we include municipality fixed effects and cluster errors at the community level, as there may be spatial correlation in the occurrence of shocks for spatially proximate households. In column 2 when we control for a number of household, dwelling, and community characteristics (average education of the household head and spouse, as well as that of their parents, as well as a rich set of dwelling characteristics like materials and access to basic services, and average rainfall in the community), the coefficient is remarkably stable.

This suggests that observables are not a particularly important factor explaining this correlation, and rather that the previous shock itself causes an increased likelihood of future shocks. So long as unobservables create a similar impact on our estimates, this is reassuring evidence that our results are unlikely to be driven by selection bias. This issue can be examined more schematically, following the approach suggested by Altonji, Elder, and Taber (2005) and recently improved upon by Oster (2013). In essence, we can ask what would be the likely amount of selection on unobservables, relative to selection on unobservables, for the main result of interest to vanish. The last two rows of Column 2 follow the latter papers and presents this proportional constant for our estimation, finding a value of 13.55 for the coefficient suggested by Altonji et al. (2005) and 6.56 for the one suggested by Oster (2013). That is, selection of unobservables would have to be more than 6.5 times more important than selection on observables for the estimated persistence to be simply an artifact of selection bias.

An alternative to controlling in a linear fashion for observables is to consider a matching estimator comparing affected households only with those unaffected yet exhibiting very similar characteristics. To implement this, we present a propensity score matching estimator in column 3, where we first estimate a propensity score for the probability of being hit by an adverse shock and then rely on the estimated propensity to define the relevant 'control' (not hit by a shock) group for each 'treatment' (hit by a shock) unit (Rosenbaum & Rubin, 1983).[4] Interestingly and in line with the results for observable selection the resulting estimate is again very stable, a 11 percentage points additional probability of future shocks for those hit prior to 2011 relative to those not hit. Thus, it appears that the linearity imposed in the ordinary least squares regressions is not very restrictive when it comes to estimating the

[4] We present results using an Epanechnikov kernel and a bandwidth of 0.06, though findings with triangular kernels and variations in the bandwidth produced similar results. Also, we impose a common support by dropping treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls. Finally, we trimmed 10 percent of the treatment observations at which the propensity score density of the control observations is the lowest. Standard errors are bootstrapped and clustered at the community level, to allow for potential correlation in the occurrence of shocks among households within given spatial proximity. All the matching estimators presented below follow these general guidelines.

likely impact of current shocks on future vulnerability. Finally, for reference and because we will use this particularly simple approach in additional regressions below, column 4 presents a simple alternative to the non-parametric matching estimator of column 3, running again a regression of shocks between 2010 and 2013 on shocks preceding 2010 but where we control directly for the propensity score (Imbens, 2004). Like every other column the estimate is quantitatively large and precisely estimated, indicating an 11 percentage point increase in future shocks.

In Panel B of Table 2 we conduct a similar exercise, but now look at a shorter-run persistence in shock incidence. More specifically, we look at the same set of regressions as in Panel A, but use a dummy for an adverse shock in 2012 as our main dependent variables and a dummy for an adverse shock one year earlier, in 2011, as our main independent variable. An advantage of this exercise is we are able to restrict attention to households who had not been previously hit by bad shocks prior to 2010. Thus, we can be more confident that these are comparable households and moreover we can control for a richer set of controls where it is now reasonable to assume that these are not affected by adverse events. A number of observables in the previous exercises of Panel A, instead, could have been affected by the shock itself and therefore cannot be treated as predetermined so we had to be very selective when choosing covariates. The main disadvantage of this exercise, however, is that we do not observe household responses to the shock in terms of relevant mechanisms like food consumption, since by the time we survey them again in 2013 the potential endogenous 2012 shocks have been realized contaminating our measure. In this sense, both exercises are complementary.

Across all columns of Panel B we see again very consistent and highly significant estimates, in this case just marginally smaller in magnitude to the longer-run effects, ranging from 8 to 9 percentage points. However, bearing in mind that average incidence of shocks in a single year, 2012, is much smaller than in the entire 2010-2013 period (about 23% of the households experience these shocks), in fact this point estimate is economically more important, amounting to an increase in mean incidence of close to 40%. The stability of the coefficients across different estimation techniques again suggests that the role of selection bias is unlikely to be a major worry, though we must point out that the Oster's proportional constant is in this case smaller, 0.43, while Altonji's coefficient keeps being sizeable at 8.07.

In Table 4 we summarize some key features of the estimation underlying the propensity score exercise of Table 2, where we model the probability of experiencing a shock as a function of the set of household, dwelling, and community predetermined characteristics. In columns

1 and 2 we show that when predicting the probability of a shock before 2010 (corresponding to Panel A of Table 2) the covariates used are jointly very significant (with a p-value of 0.002). In column 2 we report the result of running a simple OLS regression where again the incidence of shocks before 2010 is the dependent variable, and the independent variables are both the entire set of controls and the estimated propensity score. In this regression the control variables are not any more jointly or individually significant, in fact, the F-test for joint significance approaches 1. This confirms that the propensity score is doing a good job of capturing the variation in observables across households, and once controlling for it these have little predictive power. A similar exercise for the "short-run" propensity score for the probability of a shock in 2011 is reported in columns 3 and 4. Column 3 again shows that controls are jointly very significant, but column 4 confirms that they cease to have any statistical significance once we control for the propensity score.[5] In short, we have propensity scores for which a number of covariates are important in predicting adverse shocks, and which act as effective summaries of their influence according to this simple validation exercise.

To conclude, results from this section suggest that households once hit by shocks are about 11 percentage points (a 25 % increase) more likely to experience future adverse shocks than comparable households lucky enough to escape the bad draw in the first place. In the shorter horizon of one year, the similar impact of 8 percentage points implies a 36% increase relative to the mean. Moreover, the evidence suggests this is unlikely to be driven by selection bias. Next, we explore whether this persistence of bad shocks is plausibly connected to the endogenous mechanisms perpetuating vulnerability that we emphasize in our theory.

2.3 Household response to adverse shocks

Our theoretical framework suggests that certain types of households respond to adverse shocks differently than the usual literature predicts. Instead of smoothing consumption using asset holdings, they decrease their consumption significantly and maintain their level of assets, thus increasing their future vulnerability. To get a sense of whether such pattern appears in the data, we now examine the potential response of food consumption and net assets to adverse shocks. Again, the approach is to use a simple propensity score matching estimators as in Table 2 to verify how the level of food consumption and net assets of households affected with negative shocks prior to 2010 compares relative to similarly vulnerable

[5] Appendix Table A-4 presents the full estimation of the propensity score for shocks before 2010. In column 1 we model the probability of experiencing a shock before 2010 as a function of predetermined characteristics, and in column 2 we control for the propensity score. The corresponding exercise for facing a shock in 2011 is in Appendix Table A-5. In this case, we have many more possible controls.

households with better luck. We also split the sample among quintiles of wealth, where such quintiles are calculated according to a wealth index constructed as the principal component of a rich set of variables for physical assets and characteristics of the household's dwelling.

Table 4 looks at the (inverse hyperbolic sine) of reported food expenditure as a function of shock incidence. This transformation stabilizes variance and facilitates interpretation of coefficients as percentage impacts in a manner similar as the log transformation, while enabling us to cope with zero or negative values (we have similar results using a log transformation). Panel A shows the percentage change of reported food consumption in 2010 when the household experienced an adverse shock in the previous year. Interestingly, there is a significant decrease of 7 percentage points when the full sample is taken into account. However, when the sample is split in quintiles, only the fourth quintile has a significant drop in reported food expenditure of 20 percentage points, whereas the rest of households do not have a significant change.

Panel B performs a similar exercise for reported food expenditure in 2013, when the household had an adverse shock in the previous three years. This time the drop on food expenditure is not significant for the full sample nor for each quintile, although the coefficient for the fourth quintile is higher than the other coefficients. Presumably, the non-significance arises because some of these shocks happen in a longer window of time and the household had more time to adapt and smooth its consumption succesfully.

Panel C presents a stronger test for changes in food expenditure. There we examine the effect of an adverse shock on the change of reported food expenditure between 2013 and 2010. Hence, in this panel we are controlling for initial consumption values and aggregate trends over time by comparing the change in consumption of households affected by an adverse shock with the change of consumption of similar households that did not experience an adverse shock. The full sample estimation shows a larger change of consumption for households hit by an adverse shock of 5 percentage points. However, only households in the fourth quintile had a significant difference in the change of their consumption of 15 percentage points.

Table 4 shows the effect of an adverse shock on the (inverse hyperbolic sine) of net assets for 2010. Again we estimate the impact for the full sample and also for each quintile. For the full sample we estimate a decrease of net assets of the order of 177% when households are hit by an adverse shock. This reduction in assets is only significant for the first quintile, where their assets are reduced in almost 300%. However, the coefficients for the second and third quintile have an order of magnitude greater than 200%, albeit not significant most probably because of the greater variance for this categories. Remarkably, the decrease of assets for the third and fourth quintile is less than half of the magnitude of the first two quintiles. Unfortunately we cannot perform the exercises on panel B and C of Table 4 because the survey did not ask for asset information in 2013.

In sum, the results show that households in the bottom and top of the wealth distribution respond to an adverse shock by smoothing consumption using their available assets as the standard literature suggests. However, households in the middle of the wealth distribution are maintaining their assets while decreasing consumption significantly.

2.4 Consequences of privation

We now turn to the consequences of the strategies followed by the households on the persistence of adverse shocks. As highlighted in the introduction, reducing consumption levels could increase the vulnerability of a household to future adverse shocks. Perhaps a more direct way of examining the impact of different response to shocks is to think of the following thought experiment. Consider two households, similarly vulnerable yet one is struck with bad luck and other is not. Now compare the level of food consumption that they experience. Does the treated household sacrifice consumption relative to the lucky one? If so, does the treated household have a higher likelihood of future shocks?

We explore this thought experiment in the data by computing, for each treated unit, the percentage gap of its food consumption relative to its set of controls according to our propensity score estimation. Next, we divide the sample between those households which are depriving themselves from "normal consumption" defined as those reporting consumption below the one of their control counterparts (which we take to be food consumption in 'normal' times), and those not depriving themselves from normal consumption. Finally, we check the persistence of shocks for these two groups running a regression as in column 4 of of Table 2 for each sample.

The results are in Table 7 and are very revealing of the potential role of privation. The average persistence of negative shocks that we have consistently estimated at close to 11 percentage points, is entirely driven by the set of households consuming less than 'normal' levels of food per person, as judged by the comparison with the control group. Indeed, the persistence coefficient among this group suggests a larger 15 percentage point effect, whereas in the households consuming at least as much food as their controls we see a coefficient that is less than a third as large (0.04), and not statistically significant. This is entirely consistent with the idea that depriving itself from basic food consumption endogenously creates persistence in adverse shocks for households initially affected.

As a placebo test, we also perform a similar exercise for non-essential expenditures, which include expenditures on food outside home, news papers and magazines, haircuts and manicures, housemaids, books and CDs, hotels and airtickets. The idea here is to test whether a privation in this type of expenditures increases vulnerability or not. Table 4 shows that this is not the case. Remarkably, the persistence coefficient for households who decreased their expenditure in this goods and those who did not is very similar, 11 percentage points for the first group and 10 percentage points for those households who did not suffer privation of non essential goods.

This subsection shows that the future vulnerability of a household increases when its reaction after an adverse shock involves a decrease in the food expenditure. In fact, households that do not affect their consumption after a shock do not face any significant persistence. The results suggest that most of the persistence is explained by privation in food consumption and not in non essential expenditures.

3 Theory

The purpose of this section is to propose a model that captures the main findings and rationalizes the reactions of the previous section as optimal decisions. The model analyzes the decisions of a household who wants to maximize utility and faces the risk of being hit by an adverse shock each period. We assume that such shocks are persistent, that is the probability of facing an adverse shock is higher if the previous period the household also experienced an adverse shock, as in Huggett (1993). However, we depart from the usual literature by assuming that the probability of suffering an adverse shock is also endogenous; in particular, we assume that such probability is decreasing in consumption as we found in the previous section.

The household can only smooth consumption using a riskless asset, thus facing incomplete markets. Since the household cannot insure perfectly, its consumption has to decrease with a lower level of assets. Nevertheless, since a lower consumption increases the probability a future adverse shock, the household might decide to spend its assets at a higher rate to avoid a significant increase in its future vulnerability. This rational behavior could lead to a poverty trap for households having bad luck persistently since they will end up with a low level of assets and, inevitably, with low consumption which increases its vulnerability.

3.1 Model

Consider an infinitely lived household that maximizes her intertemporal discounted utility. The utility per period $u(\cdot)$ is a concave function of consumption c and the household discounts future utility at a rate β. The household receives a stochastic endowment z each period, which can take two possible values $z_L < z_H$. It can also smooth consumption using a riskless asset a that has to be greater than a natural debt limit $a_{\min}$, thus preventing Ponzi schemes. The price of such claims is q and we normalize the price of goods to 1.

The distribution of z is endogenous and persistent. According to the empirical findings, we assume that the probability of facing an adverse shock z_L, $\Pr(z_L|c,z) = P(c;z)$, is decreasing in c and z. Furthermore, we assume that such probability is not concave in c, thus generating nonconvexities in the optimal decisions.

The state variables for an agent are defined by the vector $x = (a,z) \in X = A \times Z$, where $A = [a_{\min}, \infty)$ and $Z = \{z_L, z_H\}$. Thus the household's problem can be represented in recursive formulation as:

$$v(a,z) = \max_{(c,a')\in\Gamma(x)} \{u(c) + \beta[P(c;z)\,v(a',z_L) + (1-P(c;z))\,v(a',z_H)]\}$$

where

$$\Gamma(x) = \{(c,a') : c + qa' \leq z + a, c \geq 0, a' \geq a_{\min}\}$$

is a nonempty, compact-valued and continuous correspondence.

Lemma 1 *If $a_{\min}(1-q) + z_L > 0$, there exists a unique solution $v(a,z) \in C(X)$, the space of continuous bounded functions. Moreover, such solution is strictly increasing in a and z .*

Proof. Let T be the operator defined in the recursive problem of the agent. We first want to show that $T : C(X) \to C(X)$. Fix $f \in C(X)$. First note that $\mathbb{E}[f(x)|c,z] \in C(X)$ since Z is a countable set. Since the utility function $u(\cdot)$ is assumed continuous, the operator maximizes a continuous function. A maximum exists since the correspondence $\Gamma(\cdot)$ is nonempty and compact-valued. Moreover, note that the properties of $u(\cdot)$ imply that it is bounded above, and to show that it is bounded below note that an agent will always choose $c \geq a_{\min}(1-q) + s_L > 0$, which bounds it away minus infinity. Therefore Tf is bounded. Finally, since $\Gamma(\cdot)$ is continuous, following the Theorem of the Maximum, Tf is also continuous, which proves that $T : C(X) \to C(X)$. Since the space $C(X)$ with the sup norm is a complete metric space and the Blackwell sufficient conditions (monotonicity and discounting) are satisfied, we obtain the convergence to a unique fixed point $v(\cdot)$. Since

$\Gamma(\cdot)$ is increasing in z and a and $P(c;z)$ is decreasing in z; we obtain that $v(x)$ is strictly increasing in x. ■

3.2 Calibration

We now proceed to calibrate the model according to the previous literature and the new estimates from the previous section. We first assume the utility function takes the form

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}$$

This is the standard utility function used in this type of problems. According to Mehra and Prescott (1985), estimates of the risk aversion coefficient σ are around 1.5. The endowments are calibrated to $z_H = 1$ and $z_L = 0.1$ as in Huggett (1993). The discount factor β is set to 0.95 and the price of claims $q = 0.955$ to replicate an interest rate of 4.7%.

The probability of having an adverse shock is calibrated to wander around 0.22, which is the median probability of having an adverse shock in 2012 (see Panel B of Table 2). Such probability depends on the relative consumption between a household that is hit by a shock and a similar household that do not experience such shock. As suggested by Table 7, differences in consumption levels can account for a difference in the probability of having an adverse shock of 11 percentage points. On the other hand, having a previous adverse shocks increases vulnerability in 11 percentage points according to Panel B of Table 2. Using this information and assuming symmetry over these estimations, we calibrated the transition probabilities as in Figure 1 by allowing the probability of having a bad shock to be nonconcave in consumption. In particular, we assume that the greatest difference in such probability occurs around a normalized threshold equal to 1.

3.3 Results

Figure 2 shows the optimal decision for consumption. The lack of concavity of the probability of having a bad shock as a function of consumption generates a nonconcavity of the optimal consumption. Since decreasing consumption below the threshold 1 increases its vulnerability importantly, the household tries to maintain its consumption above such threshold by decreasing its assets at a higher rate. However, for a sufficiently low level of assets, it becomes too costly to maintain such level of consumption and the household optimally decreases its consumption significantly below this threshold, and it continues to decrease it as the level of assets decreases. This significant decrease that generates the nonconcavity in the consumption policy is precisely captured in Column 4 of Table 4 for households in the fourth quintile. This in turn suggests that at this level of consumption occurs the significant change in the probability of facing an adverse shock.

This behavior could lead to a poverty trap that can be observed in Figure 3, which shows the optimal policy for future assets. Note that when a household experiences an adverse shock, it always decreases his assets in order to smooth consumption. On the other hand, when the household is not hit by an adverse shock, the household saves at a low level of assets and at a high level of assets. However, there is an intermediate set of values where the household does not save, i.e. its consumption policy is at or below the 45 degree line. This region is precisely where consumption is not concave and arises because all the endowment and some of the assets are used to maintain a level of consumption above the threshold.[6]

This poverty trap is consistent with stories where poorer households with low levels of consumption and debt that do not experience adverse shocks for some time are able to repay their debt, and after repaying it, they inmediately incur in a new debt to increase their level of consumption above the threshold that makes them more vulnerable. This fact is impossible to obtain with standard theories that assume completely exogenous shocks. To scape this region it will be necessary for a household in this region to continue having good luck for several periods, since an adverse shock would lead to a new loss of assets and a decrease in consumption that will again increase their vulnerability.

The model and the empirical results together suggest that urban Colombian households in the first two quartiles are in a poverty trap, whereas those in the third quartile are vulnerable to also get trapped in it. Finally, Figure 4 shows that welfare losses are very large for households that are close to the debt limit and experience an adverse shock. According to the calibration, these households may have only 5% of the welfare of a household with the same level of assets that did not face an adverse shock. This losses are higher than the ones found in standard models because these households would be more dynamically vulnerable that richer households that are able to maintain theit consumption above the threshold.

4 Concluding remarks

In this paper we first document empirical facts on how persistent adverse shocks are, how households react when facing such shocks, and how endogenous these shocks are to those

[6]The key assumption to obtain the poverty trap is the strong nonconcavity of the probability of facing an adverse shock. Zambrano (2015) analyses a model where the probability of being employed is an increasing and concave function of effort. He shows that the optimal policy for assets and consumption has a similar shape to the corresponding policy of a model where shocks are exogenous. These optimal policies suggest that consumption is a concave function of assets and therefore households always save when they get a good realization of the endowment until a unique endogenous upper bound, thus poverty traps do not arise.

responses. We showed that having a shock increases the likelihood of having a future adverse shock by about 8 to 11 percentage points depending on the time horizon we examine. We also showed that households in the fourth quintile of the wealth distribution decrease their consumption significantly by 20 percentage points when hit by an adverseshock, relative to those that do not experience bad luck. On the other hand, households in the bottom and top of the wealth distribution are able to smooth consumption relatively well with their assets, as the standard literature suggests. Thirdly, we show that persistence of bad shocks is 11 percentage points higher for households that decreased their consumption, compared to those that did not, therefore suggesting that the persistence of adverse shocks is mostly an endogenous phenomenon.

We then propose a model that incorporates these findings and rationalizes the optimal responses of households. The model is a standard Bewley framework, except that the transition among states is endogenous. Following the empirical findings, we assume the probability of having an adverse shock is decreasing in consumption and persistent, and we calibrate it accordingly using our estimates. The model predicts that optimal consumption is not concave around the threshold where the probability of facing an adverse shock increases significantly. This is optimal since households avoid as much as possible having a consumption below such threshold by using assets more intensively. However, this generates a poverty trap because households with debt that are sufficiently "lucky" to not experience adverse shocks and are to able to repay their debt, will incur again in new debt to increase their consumption above the threshold and avoid the increased vulnerability. The empirical results and the model suggest that households in the first and second quintile are in a poverty trap. Finally, taking into account the endogeneity of the distribution of shocks to consumption choices imply higher welfare losses than the ones obtain with standard models with completely exogenous shocks.

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Table 1: Descriptive statistics, main variables
Colombian urban households

	Full sample			Above median wealth index			Below median wealth index		
Variable	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**
Adverse shocks									
Prior to 2010	0.32	0.47	4131	0.31	0.46	2055	0.34	0.47	2076
Between 2010 and 2013	0.49	0.5	4131	0.45	0.5	2055	0.54	0.5	2076
In 2011	0.16	0.37	4131	0.15	0.35	2055	0.17	0.38	2076
In 2012	0.25	0.43	4131	0.22	0.42	2055	0.27	0.44	2076
Household behavior, 2010									
Reported food expenditure	97323	66155	4131	119757	833333	2055	75115	46236	2076
Net assets	889859	10163812	3833	1967441	13464349	1861	-127068	5256492	1972

Table 2: Persistence of negative shocks
Colombian urban households

	(1)	(2)	(3)	(4)
Estimation method:	OLS	OLS + Controls	Matching	OLS
Panel A: Dependent variable is Adverse Shocks between 2010 and 2013				
Adverse shocks prior to 2010	0.12***	0.12***	0.11***	0.11***
	(0.02)	(0.02)	(0.02)	(0.0216)
Propensity Score				0.294**
				(0.138)
Observations	2,876	2,876	2769	2,769
R^2	0.03	0.06		0.031
Dependent variable...				
Mean	0.44	0.44	0.44	0.44
Standard deviation	0.50	0.50	0.50	0.50
Unobservable selection...				
Altonji		13.55		
Oster		6.56		
Panel B: Dependent variable is Adverse Shocks in 2012				
Adverse Shocks in 2011	0.09***	0.08***	0.08***	0.08***
	(0.03)	(0.03)	(0.03)	(0.03)
Propensity Score				0.42**
				(0.17)
Observations	2,801	2,801	2715	2,715
R^2	0.03	0.04		0.03
Dependent variable...				
Mean	0.23	0.23	0.22	0.22
Standard deviation	0.42	0.42	0.42	0.42
Unobservable selection...				
Altonji		8.07		
Oster		0.43		

Notes: Standard errors in parentheses, clustered at the community level (bootstrapped for the matching estimators). *** p<0.01, ** p<0.05, * p<0.1. Regressions at the household level, including municipality fixed effects. the sample is restricting to households in the same dwelling for more than two years (Panel A) and restricting to households that did not suffer from any adverse shocks 12 months before ELCA 2010 (Panel B). In column 4 we control for the propensity score underlying the corresponding matching estimator of column 3. Controls for regressions and propensity scores in Panel A: Average years of education , Average can read & write , Vulnerable location , Floor made of brick , Floor made of cement or gravel , Floor made of wood in bad condition, dust, other , Walls made of blocks, bricks, stone, wood , Natural gas , Aqueduct , Sewage , Phone , Garbage collection , Garbage picked by cleaning services , Toilet connected to sewage or septic tank , Water from public aqueduct , Natural gas for cooking , Propane gas for cooking , Kerosene, oil, petroleum or *cocinol* for cooking , Exclusive kitchen , Room for cooking , Average precipitation. Controls for regressions and propensity scores in Panel B are: Average years of education , HH Income , Number of stereos , House ownership , Floor made of brick , Floor made of cement or gravel , Floor made of wood in bad contigion, dust, other , Walls made of blocks, bricks, stone, wood , Number of household members , Owes money , Beneficiary of Familias en Accion , Number of buildings owned , Number of fridges , Number of washing machines , Number of blenders , Number of ovens , Number of microwaves , Located near a spout , Number water heaters , Number showers , Number air conditioners , Owns Government bonds , Average precipitations, Vulnerable location , Average can read & write. Unobserved Selection is the degree of selection on unobservables relative to observables which would be necessary to explain away the main result

Table 3: Balance in covariates
Joint significance in Probit's marginal effects for covariates

	Long-run Propensity Score		Short-run Propensity Score	
	Controls Only	Controls + Pscore	Controls Only	Controls + Pscore
P-value joint significance of controls	0.0002	0.95	0.007	0.93

Table 4: Household food consumption response to adverse shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	Matching	Matching	Matching	Matching	Matching	Matching
Panel A: Dependent variable is (the inverse hyperbolic sine of) reported food expenditure in 2010						
Adverse Shock Prior to 2010	-0.07**	-0.06	0.01	-0.09	-0.20***	-0.09
	(0.03)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
Percentile	Full sample	0-20	20-40	40-60	60-80	80 -100
Observations	2769	520	514	502	546	477
Dependent variable...						
Mean	103,474	65,110	82,618	103,119	123,417	147,474
Standard Deviation	71,131	40,520	50,255	59,081	76,706	85,570
Panel B: Dependent variable is (the inverse hyperbolic sine of) reported food expenditure in 2013						
Adverse Shock between 2010 and 2013	-0.03	0.01	-0.04	-0.00	-0.07	-0.02
	(0.02)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)
Percentile	Full sample	0-20	20-40	40-60	60-80	80 -100
Observations	2674	513	547	500	521	502
Dependent variable...						
Mean	116,418	84,129	101,797	1139,423	126,068	159,349
Standard Deviation	80,784	52,447	61,260	65,615	77,145	117,251
Panel C: Dependent variable is Δ (the inverse hyperbolic sine of) reported food expenditure in 2013						
Adverse Shock between 2010 and 2013	-0.05*	-0.00	-0.09	0.01	-0.15*	-0.00
	(0.03)	(0.07)	(0.07)	(0.07)	(0.06)	(0.08)
Percentile	Full sample	0-20	20-40	40-60	60-80	80 -100
Observations	2,678	515	546	502	520	503
Dependent variable...						
Mean	116,418	84,129	101,195	114,453	126,016	159,274
Standard Deviation	80,784	52,447	58,510	68,256	77,051	117,152

Notes: Bootstrap Standard Errors are clustered at the community level.*** p<0.01, ** p<0.05, * p<0.1. Regressions are at the household level, restricting to households remaining in the same dwelling for more than two years. Every regression controls for: Average education level 2010, Education level of father 2010, Education level of mother 2010, Average can write & read 2010, Vulnerable location 2010, Floor material 2010, Wall material 2010, Electricity 2010, Natural gas 2010, Aqueduct 2010, Sewer 2010, Phone 2010, Garbage collection 2010, Garbage elimination 2010, Sanitary service 2010, Water 2010, Cooking energy 2010, Exclusive kitchen 2010, Room for food 2010, Average precipitation, and fixed effects at the municipal level. Percentile is the corresponding percentile in the wealth index constructed as the principal component of a rich set of variables for physical assets and characteristics of the household's dwelling. Full details in Appendix Table A-1.

Table 5: Household net assets response to adverse shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	Matching	Matching	Matching	Matching	Matching	Matching
Dependent variable is (the inverse hyperbolic sine of) net assets in 2010						
Adverse Shock prior to 2010	-1.77***	-2.96**	-2.61	-0.71	-1.28	-2.13
	(0.66)	(1.30)	(1.73)	(1.61)	(1.60)	(1.65)
Percentile	Full sample	0-20	20-40	40-60	60-80	80 -100
Observations	2556	477	478	462	501	431
Dependent variable...						
Mean	1,163,218	45,419	97,077	321,664	1,141,447	4,606,299
Standard Deviation	7,966,533	801,223	2,761,156	4,387,937	6,413,393	16,310,152

Bootstrap Standard Errors are clustered at the community level.*** p<0.01, ** p<0.05, * p<0.1. Regressions are at the household level, restricting to households remaining in the same dwelling for more than two years. Every regression controls for: Average education level 2010, Education level of father 2010, Education level of mother 2010, Average can write & read 2010, Vulnerable location 2010, Floor material 2010, Wall material 2010, Electricity 2010, Natural gas 2010, Aqueduct 2010, Sewer 2010, Phone 2010, Garbage collection 2010, Garbage elimination 2010, Sanitary service 2010, Water 2010, Cooking energy 2010, Exclusive kitchen 2010, Room for food 2010, Average precipitation, and fixed effects at the municipal level. Percentile is the corresponding percentile in the wealth index constructed as the principal component of a rich set of variables for physical assets and characteristics of the household's dwelling. Full details in Appendix Table A-1.

Table 6: Household privation of food expenditures and persistence of adverse shocks

	(1)	(2)	(3)
Dependent variable is Adverse Shocks between 2010 and 2013			
Food Privation	Full sample	No privation	Privation
Adverse Shocks prior to 2010	0.11***	0.04	0.15***
	(0.02)	(0.03)	(0.02)
Propensity Score	0.29**	0.30*	0.23
	(0.14)	(0.16)	(0.14)
Observations	2,769	2,228	2,479
R^2	0.03	0.02	0.03
Dependent variable...			
Mean	0.44	0.44	0.44
Standard Deviation	0.50	0.5	0.5

Notes: Robust standard errors are clustered at the community level. *** p<0.01, ** p<0.05, * p<0.1. Propensity score for each regression is based on the same set of variables as in Table A-4. Column (1) reports the estimates using full sample, column (2) for households whose food expenditures are at least as large as those of control households as determined by the propensity score matching procedure, column (3) reports estimates whose food expenditures is less than that of control households as determined by the propensity score matching procedure. Household level regressions restricted to households in the same dwelling for more than two years.

Table 7: Household privation of non essential expenditures and persistence of adverse shocks

	(1)	(2)	(3)
Dependent variable is Adverse Shocks between 2010 and 2013			
Non Essential Privation	Full sample	No privation	Privation
Adverse Shocks prior to 2010	0.11***	0.10**	0.11***
	(0.02)	(0.04)	(0.02)
Propensity Score	0.29**	0.23	0.27*
	(0.14)	(0.16)	(0.14)
Observations	2,769	2,097	2,606
R^2	0.03	0.02	0.03
Dependent variable...			
Mean	0.44	0.44	0.44
Standard Deviation	0.50	0.5	0.5

Notes: Robust standard errors are clustered at the community level. *** p<0.01, ** p<0.05, * p<0.1. Propensity score for each regression is based on the same set of variables as in Table A-4. Column (1) reports the estimates using full sample, column (2) for households whose food expenditures are at least as large as those of control households as determined by the propensity score matching procedure, column (3) reports estimates whose non essential expenditures is less than that of control households as determined by the propensity score matching procedure. Household level regressions restricted to households in the same dwelling for more than two years.

Figure 1: Probability of a Bad Shock

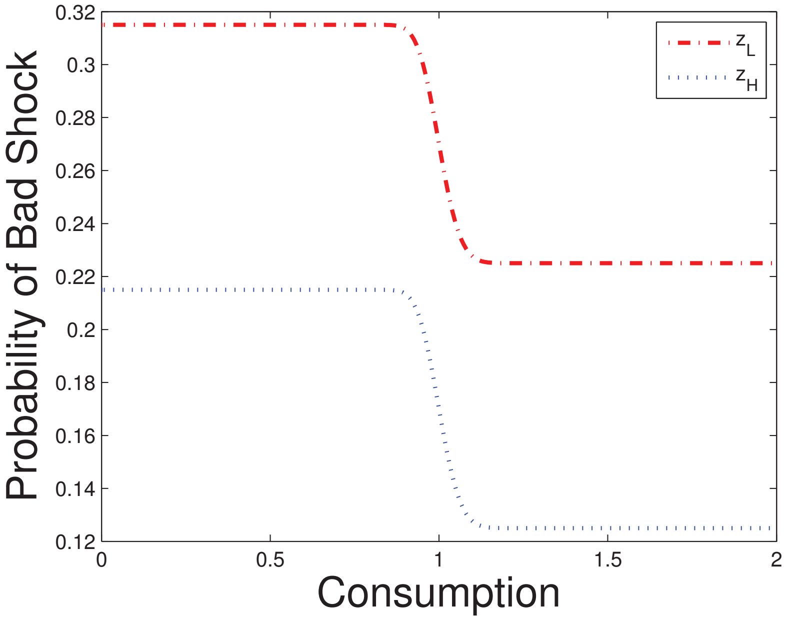

Figure 2: Optimal policy for consumption

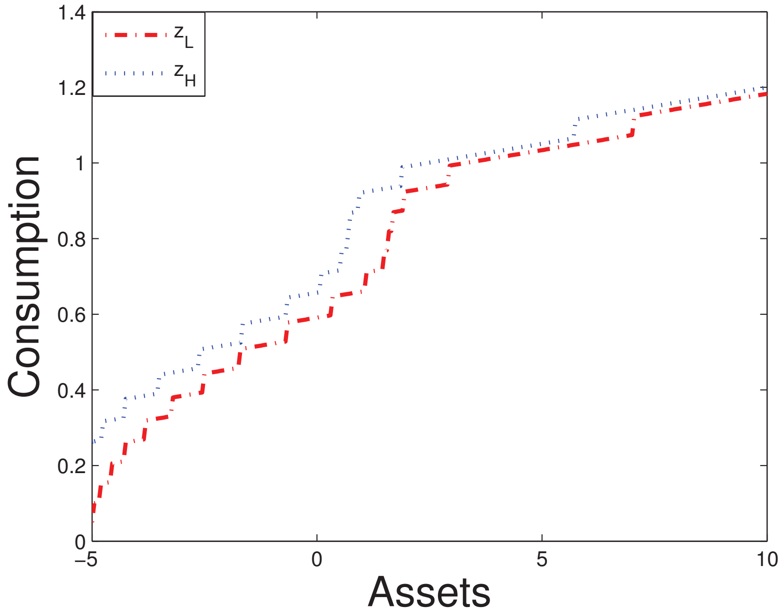

Figure 3: Optimal policy rule for assets

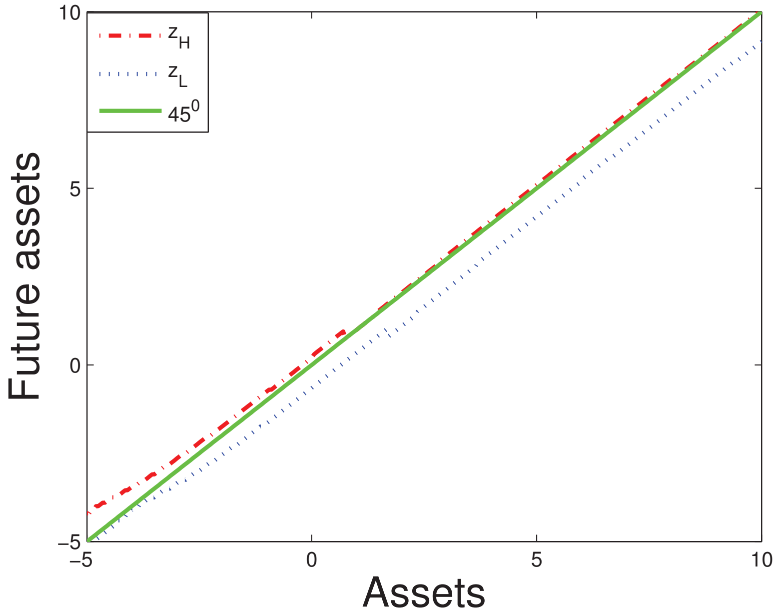

Figure 4: Welfare losses with an adverse shock

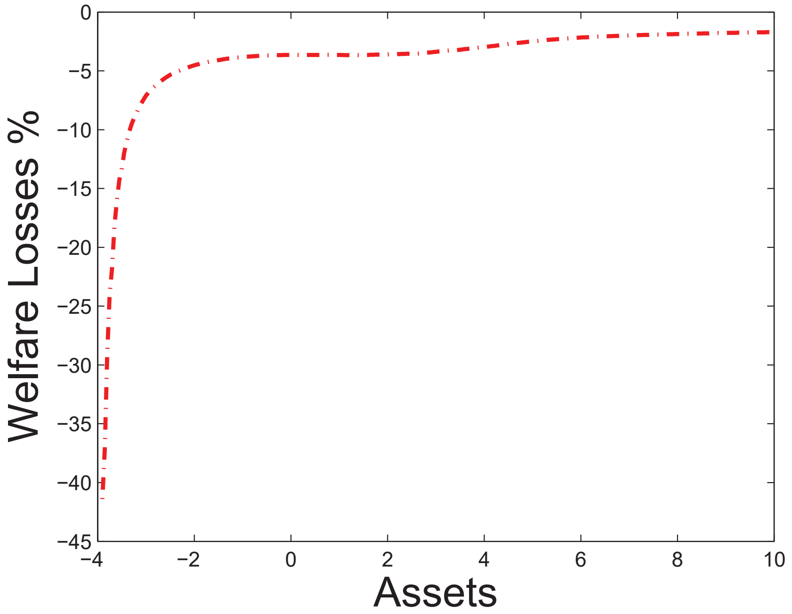

Table A-1: Variable definitions

Variable name	Description
Adverse shocks prior 2010	Binary variable. Equals 1 if the household reports experiencing shocks within the past 12 months before the 2010 wave of the survey. Households are asked to indicate whether they were affected by any of the following: illness of any member obstructing their normal activities, accident of any member obstructing their normal activities, death of the household head or spouse, death of other member of the household, abandonment by household head or spouse, abandonment by under age, divorce of spouses, household head or spouse lost its job, other family member lost its job, forced to leave usual dwelling, bankruptcy of closing of family businesses, loss of dwelling, loss of remittances, burgarly, fires or destruction of household goods, violence.
Adverse shocks between 2010 and 2013 Adverse shocks in 2011 and in 2012	Binary variable. Equals 1 if the household reports experiencing shocks between 2010 and 2013. The set of circumstances are the same as those asked in 2010 (see above), plus whether the households suffered from floods or landslides, gales, or earthquakes. Households are also asked about the importance of the event, and we restrict attention to adverse shocks which the household declares had intermediate or strong effects on its stability (excluding only the low category). The month and year of such intermediate or strong shocks are also specified, and we use this to construct a similar dummy variable for shocks in 2011 and in 2012.
Food expenditure per person, 2010	Household declared monthly total expenditure in food, divided by total members of the household.
Wealth quartiles, 2010	We construct a wealth index using the first principal component of a number of variables capturing household wealth, including the following. Dummy variables for adequate: floor materials, wall materiales, garbage collection, access to water, access to sanitation, cooking fuel; access to electricity and telephone service; ownership of household appliances (refrigerators, washing machines, blenders, stoves, microwaves, water heating, showers, air conditioning, radio, television, stereo systems, video players, computers); access to cable television and internet; number of rooms to sleep; and ownership of bicycles, motor bikes, and cars. Quartiles refer to quartiles of distribution of this index.
Assets	Sum of: money in banks, corporations or cash, pension funds, severance money, stock or bonds in the private sector, capital or investments in companies, money in saving groups or "roscas", money lent, land plots, housing properties, office equipment, motorcycles, cars, other goods, animal stock, machines, transportation goods.
Debts	Sum of all household declared debts from all sources.
Net assets per person	$\frac{\text{Assets - Debt}}{\text{Number of people in the household}}$
Average education level	Average education level of the head of the household and spouse.
Education level of father	Average education level of the fathers of: head of the household and spouse.

Continued on next page

Table A-1 Variable definitions – *Continued from previous page*

Variable name	Description
Education level of mother	Average education level of the mothers of: of: head of the household and spouse.
Average literacy	Average of dummy variable for knowing to read and write, household and spouse.
Vulnerable location	Binary variable. Equals 1 if the household is near a rubbish dump, factory or industry, sewage pipes, waste water treatment plant, route of hydrocarbons transportation, or high-voltage energy line.
Floor material	Categorical variable for quality of floor material. Equals: 1 if floor is made of carpets, marble, parquet or polished floor; 2 if floor is made of ceramic tiles, vinyl, "tableta", or bricks; 3 if floor is made of cement or gravel; 4 if floor is made of wood in bad condition, rough wood or wooden plank, or dust, or other materials.
Floor made of brick	Dummy variable that equals 1 if the categorical variable Floor material 2010 is 2
Floor made of cement or gravel	Dummy variable that equals 1 if the categorical variable Floor material 2010 is 3
Floor made of wood in bad condition, dust, other	Dummy variable that equals 1 if the categorical variable Floor material 2010 is 4
Wall material	Categorical variable for quality of wall material. Equals: 1 if walls are made of bricks or polished wood; 2 if walls are made of *tapia pisada*; 3 if walls are made of *bahereque*; 4 if walls are made of prefabricated material; 5 if walls are made of wood in bad condition or *tabón*, 6 if walls are made of bamboo, cane, *esterilla*, or other plant; 7 if walls are made of zinc, fabric, cans, or any waste.
Walls made of blocks, bricks, stone, wood	Dummy variable that equals 1 if the categorical variable Wall material 2010 is 1
Electricity	Binary variable. Equals 1 if the household has electricity service
Natural gas	Binary variable. Equals 1 if the household has natural gas service connected to the public net.
Aqueduct	Binary variable. Equals 1 if the household has aqueduct service.
Sewage	Binary variable. Equals 1 if the household has sewage service.
Phone	Binary variable. Equals 1 if the household has phone services.
Garbage collection	Binary variable. Equals 1 if the household has garbage collection services.
Garbage picked by cleaning services	Binary variable. Equals 1 if garbage is picked by cleaning services
Toilet connected to sewage or septic tank	Binary variable. 1 if the household has a toilet connected to the sewage or a septic tank

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Table A-1 Variable definitions – *Continued from previous page*

Variable name	Description
Water from public aqueduct	Binary variable. 1 if water is collected from public aqueduct
Cooking energy	Categorical variable which equals: 1 if the household uses electricity for cooking; 2 if the household uses natural gas for cooking; 3 if the household uses propane gas for cooking; 4 if the household uses kerosene, oil, petroleum or *cocinol* for cooking; 5 if the household uses wood for cooking; 6 if the household uses mineral carbon for cooking; 7 if the household uses disposal material for cooking.
Natural gas for cooking	Binary variable. 1 if the categorical variable Cooking energy 2010 is 2.
Propane gas for cooking	Binary variable. 1 if the categorical variable Cooking energy 2010 is 3.
Kerosene, oil, petroleum or *cocinol* for cooking	Binary variable. 1 if the categorical variable Cooking energy 2010 is 4.
Exclusive kitchen	Binary variable. Equals 1 if household prepares food in area of exclusive use.
Room for cooking	Binary variable. Equals 1 if there is a room used exclusively for cooking.
Average precipitation	Average of monthly precipitation next to the closets IDEAM station for the years 1980-2009.
HH Income	Reported income from work, pensions, other income, dividends, rents, help from other HHs. All the values were divided by the number of members of the HH.
Number of stereos	Reported number of stereos owned by the HH.
House ownership	Binary variable. Equals 1 if the household owns the household. Also 1 if the household is paying mortgage.
Number of household members	Reported number of household members
Owes money	Binary variable. Equals 1 if the household owns money.
Beneficiary of Familias en Accion	Binary variable. Equals 1 if the household reported being beneficiary of the social program called Familias en Accion.
Number of buildings owned	Reported number of buildings (different from the own dwelling) owned by the household.
Number of fridges	Reported number of fridges.
Number of washing machines	Reported number of washing machines.
Number of blenders	Reported number of blenders.
Number of ovens	Reported number of ovens.
Number of microwaves	Reported number of microwaves.
Located near a spout	Binary variable. 1 if the household is located near a spout.

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Table A-1 Variable definitions – *Continued from previous page*

Variable name	Description
Number water heaters	Reported number of microwaves.
Number showers	Reported number of showers.
Number air conditioners	Reported number of air conditioners.
Owns Government bonds	Binary variable. 1 if the household owns any Government bond.

Notes: Source is the Colombian Longitudinal Survey (Encuesta Longitudinal de la Universidad de los Andes, ELCA), except from rainfall which is from the Colombian Metereological Institute, IDEAM. All monetary values are expressed in Colombian pesos.

Table A-2: Descriptive statistics, control variables
Colombian urban households

	Full sample			Above median wealth index			Below median wealth index		
Variable	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**
Household characteristics, 2010									
Education									
Average years of education	8.35	4.21	4131	9.84	4.08	2055	6.91	3.81	2076
Literacy	0.95	0.19	4131	0.98	0.12	2055	0.92	0.24	2076
Vulnerable location	0.33	0.47	4131	0.32	0.47	2055	0.34	0.47	2076
Floor material									
Brick, tables, or vinyl	0.55	0.5	4131	0.74	0.44	2055	0.36	0.48	2076
Cement or gravel	0.33	0.47	4131	0.15	0.36	2055	0.51	0.5	2076
Wood in bad condition, dust, other	0.06	0.24	4131	0.02	0.15	2055	0.1	0.29	2076
Walls material									
Blocks, bricks, stone or wood	0.93	0.26	4131	0.97	0.16	2055	0.88	0.32	2076
Household's services									
Natural gas	0.69	0.46	4131	0.79	0.41	2055	0.6	0.49	2076
Aqueduct	0.96	0.19	4131	0.99	0.1	2055	0.94	0.24	2076
Sewage	0.91	0.28	4131	0.98	0.15	2055	0.85	0.35	2076
Phone	0.52	0.5	4131	0.75	0.43	2055	0.29	0.45	2076
Garbage picked by cleaning services	0.98	0.14	4131	0.99	0.1	2055	0.97	0.16	2076
Toilet connected to sewage or septic tank	0.98	0.14	2876	0.99	0.1	1432	0.97	0.17	1444
Garbage collection	0.98	0.15	4131	0.99	0.07	2055	0.96	0.2	2076
Water from public aqueduct	0.91	0.29	2876	0.97	0.17	1432	0.85	0.36	1444
Natural gas for cooking	0.65	0.48	4131	0.74	0.44	2055	0.56	0.5	2076
Propane gas for cooking	0.27	0.44	4131	0.2	0.4	2055	0.34	0.47	2076
Kerosene, oil, petroleum or *cocinol* for cooking	0.03	0.16	4131	0.01	0.08	2055	0.05	0.22	2076
Exclusive kitchen	0.93	0.26	4131	0.97	0.18	2055	0.89	0.31	2076
Room for cooking	0.94	0.25	4131	0.98	0.15	2055	0.89	0.31	2076
Average Precipitation	74.61	53.57	4131	72.51	54.86	2055	76.7	52.21	2076
HH Income	328759.4	338869.17	4131	456524.9	411362.8	2055	202286.32	169944.69	2076
Number of stereo	0.63	0.58	4131	0.91	0.5	2055	0.35	0.53	2076
House ownership	1.54	0.5	4131	1.47	0.5	2055	1.61	0.49	2076
Number of household member	4.38	2.01	4131	1.77	2	4.46	2.21	2	
Owes mone	0.63	0.48	4131	0.66	0.47	2055	0.6	0.49	2076
Beneficiary of Familias en Accion	0.22	0.42	4131	0.08	0.27	2055	0.36	0.48	2076
Number of buildings owned	0.05	0.25	4131	0.08	0.31	2055	0.02	0.17	2076
Number of fridges	0.85	0.4	4131	1.02	0.21	2055	0.68	0.47	2076
Number of washing machines	0.59	0.55	4131	0.91	0.44	2055	0.27	0.45	2076
Number of blenders	0.88	0.36	4131	1	0.22	2055	0.76	0.43	2076
Number of ovens0	0.33	0.57	4131	0.61	0.67	2055	0.05	0.21	2076
Number of microwaves	0.27	0.55	4131	0.53	0.68	2055	0.02	0.13	2076
Located near a spout	0.2	0.4	4131	0.17	0.38	2055	0.24	0.42	2076
Number water heater	0.17	0.53	4131	0.34	0.71	2055	0	0.06	2076
Number showers	0.27	0.56	4131	0.49	0.70	2055	0.06	0.23	2076
Number air conditioners	0.22	0.62	4131	0.34	0.76	2055	0.09	0.41	2076
Owns Government bonds	0.01	0.08	4131	0	0.04	2055	0.01	0.11	2076

Table A-3: Shocks to Households
Elca, 2010 and 2013

	Prior 2010		Between 2010 & 2013	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Type of shock:				
Disease or accident	0.15	0.36	0.21	0.41
Death or abandonment of any member of the household	0.03	0.16	0.03	0.17
Spouses separation	0.02	0.13	0.04	0.2
Any member of the family lost a job	0.11	0.32	0.22	0.42
Forced to leave dwelling	0.01	0.11	0.04	0.2
Asset loss	0.05	0.22	0.14	0.34
Victim of violence	0.01	0.11	0.01	0.12
Placement of a new member of the household	0.05	0.22	0.04	0.2

Table A-4: Propensity score estimation and validation Probability of a shock before 2010

	(1)	(2)	(3)
Estimation Method	Probit	OLS	Probit
Average years of education	0.01	0.00	0.01
	(0.01)	(0.00)	(0.00)
Average can read & write	0.02	0.00	0.01
	(0.16)	(0.05)	(0.05)
Vulnerable location	0.31***	0.07	0.25*
	(0.06)	(0.06)	(0.13)
Floor made of brick	0.19	0.03	0.13*
	(0.12)	(0.05)	(0.07)
Floor made of cement or gravel	0.32**	0.06	0.24*
	(0.13)	(0.07)	(0.13)
Floor made of wood in bad condition, dust, other	0.07	0.01	0.05
	(0.18)	(0.06)	(0.07)
Walls made of blocks, bricks, stone, wood	-0.22*	-0.05	-0.19*
	(0.12)	(0.06)	(0.11)
Natural gas	0.34*	0.06	0.22**
	(0.19)	(0.08)	(0.10)
Aqueduct	0.13	0.02	0.08
	(0.28)	(0.08)	(0.09)
Sewage	0.27	0.05	0.16*
	(0.27)	(0.09)	(0.09)
Phone	-0.09	-0.02	-0.07*
	(0.06)	(0.03)	(0.04)
Garbage collection	0.04	0.02	0.03
	(0.44)	(0.12)	(0.14)
Garbage picked by cleaning services	-0.08	-0.03	-0.07
	(0.31)	(0.09)	(0.12)
Toilet connected to sewage or septic tank	-0.20	-0.05	-0.16
	(0.23)	(0.09)	(0.12)
Water from public aqueduct	0.09	0.02	0.07
	(0.24)	(0.07)	(0.09)
Natural gas for cooking	0.08	0.01	0.05
	(0.15)	(0.05)	(0.06)
Propane gas for cooking	0.45***	0.08	0.35*
	(0.17)	(0.08)	(0.18)
Kerosene, oil, petroleum or *cocinol* for cooking	0.70***	0.12	0.54***
	(0.26)	(0.13)	(0.20)
Exclusive kitchen	-0.04	-0.01	-0.03
	(0.11)	(0.04)	(0.04)
Room for cooking	0.11	0.02	0.07
	(0.14)	(0.05)	(0.05)
Average precipitation	-0.00	-0.00	-0.00*
	(0.00)	(0.00)	(0.00)
Propensity score		0.37	-1.20
		(0.59)	(1.09)
Constant	-1.03*	0.12	
	(0.63)	(0.22)	
Observations	2,855	2,855	2,855
R^2		0.08	
P-value joint significance	0.0002	0.99	0.95

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include municipality fixed effects. The p-value is for joint significance of every variable, excluding the fixed effects and propensity score.

Table A-5: Propensity score estimation and validation Probability of a shock in 2011

Estimation Method	(1) Probit	(2) OLS	(3) Probit (marginal effects)
Average years of education	0.01	0.00*	0.01**
	(0.01)	(0.00)	(0.00)
HH Income	-0.00*	-0.00**	-0.00***
	(0.00)	(0.00)	(0.00)
Number of stereos	-0.06	-0.02	-0.04**
	(0.06)	(0.02)	(0.02)
House ownership	-0.00	-0.00	-0.00
	(0.06)	(0.01)	(0.01)
Floor made of brick	-0.02	-0.00	-0.01
	(0.13)	(0.03)	(0.03)
Floor made of cement or gravel	0.04	0.01	0.03
	(0.14)	(0.03)	(0.03)
Floor made of wood in bad contigion, dust, other	0.27	0.09	0.22**
	(0.18)	(0.06)	(0.11)
Walls made of blocks, bricks, stone, wood	-0.04	-0.00	-0.01
	(0.13)	(0.03)	(0.03)
Number of household members	0.02	0.00	0.01*
	(0.02)	(0.00)	(0.01)
Owes money	0.18***	0.06**	0.10***
	(0.06)	(0.03)	(0.03)
Beneficiary of Familias en Accion	0.07	0.02	0.04
	(0.09)	(0.02)	(0.03)
Number of buildings owned	-0.03	-0.01	-0.02
	(0.15)	(0.03)	(0.03)
Number of fridges	-0.04	-0.01	-0.02
	(0.09)	(0.02)	(0.02)
Number of washing machines	0.26***	0.09**	0.15***
	(0.07)	(0.04)	(0.05)
Number of blenders	0.07	0.02	0.04*
	(0.09)	(0.02)	(0.02)
Number of ovens	-0.10	-0.04*	-0.06**
	(0.08)	(0.02)	(0.02)
Number of microwaves	0.04	0.02	0.03
	(0.09)	(0.02)	(0.02)
Located near a spout	0.13	0.04	0.09*
	(0.12)	(0.03)	(0.04)
Number water heaters	-0.04	-0.02	-0.03
	(0.10)	(0.02)	(0.02)
Number showers	-0.02	-0.01	-0.01
	(0.08)	(0.02)	(0.02)
Number air conditioners	-0.08	-0.03*	-0.05**
	(0.07)	(0.02)	(0.02)
Owns Government bonds	-0.10	-0.08	-0.08
	(0.47)	(0.11)	(0.06)
Average precipitations	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
Vulnerable location	0.04	0.02	0.03
	(0.10)	(0.02)	(0.02)
Average can read & write	-0.02	-0.02	-0.02
	(0.18)	(0.04)	(0.04)
Propensity Score		-0.94	-1.93**
		(0.61)	(0.76)
Constant	-1.44***	0.16	
	(0.41)	(0.10)	
Observations	2,755	2,715	2,704
R^2		0.02	
P-value joint significance	0.007	0.99	0.93

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include municipality fixed effects. P-value joint significance is the p-value of joint significance of the marginal effects for every variable, excluding the fixed effects and propensity score.