Endogenous Persistent Shocks and Households' Welfare*

Mateo Arbelaez† Leopoldo Fergusson‡ Andres Zambrano §

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Abstract

This paper estimates the persistence of adverse shocks and how this depends on household consumption decisions. We document how households respond to adverse shocks and present a model that builds on these estimates and rationalizes the observed behavior. Using Colombian data for urban households, we find that shocks are quite persistent: having an adverse shock increases future vulnerability by about 9 to 11 percentage points. Also, we show households in the middle of the wealth distribution significantly decrease consumption when hit by an adverse shock. Finally, our estimates indicate that this consumption reduction increases persistence of adverse shocks by 9 percentage points. When introduced in a calibrated version of our theoretical model, these numbers suggest there exists a poverty trap for households in the first two quartiles, and implies very large welfare losses for the first quartile when hit by an adverse shock.

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

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†Universidad de los Andes, Facultad de Economía, Cra 1 N^o 18A - 12 Bogotá, Colombia. E-mail: m.arbelaez342@uniandes.edu.co

‡Universidad de los Andes, Facultad de Economía, Cra 1 N^o 18A - 12 Bogotá, Colombia. E-mail: lfergusson@uniandes.edu.co

§Universidad de los Andes, Facultad de Economía, Cra 1 N^o 18A - 12 Bogotá, Colombia. E-mail: ja.zambrano@uniandes.edu.co

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, quantify their effect on household's welfare, and identify if there is a poverty trap. Since they are most important for welfare and from a policy perspective, we focus on the circumstances and reactions that are likely to create increased vulnerability and persistent poverty (or, in the extreme case, poverty traps). The paper thus falls in line with a long tradition in development economics studying the possibility of poverty traps.

While the evidence on their existence has remained remarkably elusive (? (?); ? (?)), one reason is that most of the literature has focused on estimating asset accumulation equations in search of sufficiently strong nonconvexities. As emphasized in ? (?), 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 falls in this tradition.

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 (? (?); ? (?)). 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, 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

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 first Household Panel Survey, ELCA, to measure the persistence of adverse shocks and how such persistence depends on consumption decisions.[3] 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 third quartile of the wealth distribution decrease consumption significantly after being hit by an adverse shock.

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. We show how poverty traps can arise when the probability of facing an adverse shock exhibits a nonconvexity that increases importantly such probability if consumption falls below a threshold. The intuition is that households will try to maintain their consumption above such threshold by sacrificing assets at a higher rate. This behavior could create a poverty trap (indeed it does under our calibration) because poorer households would not be able to accumulate assets above some intermediate level, and will repeatedly have a consumption level that perpetuates their vulnerability. Combining these theoretical results with the empirical estimates suggests that urban Colombian households in the first two quartiles are currently trapped in poverty. Moreover, households in the first quartile that experience an adverse shock are having huge welfare losses when compared to households that do not face such shock.

The organization of the paper is as follows. The next section explores how persistent and endogenous are adverse shocks, and how households modify their consumption when

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

[3] The ELCA just completed its first follow-up, in 2013, following the baseline measure in 2010. It is worth noting that the traditional approach to identify poverty traps typically requires longer panels to be convincing. However, even with just two time periods we will be able to directly test for the presence of our purported dynamic mechanisms.

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, households in the middle of the wealth distribution appear to sacrifice consumption. 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 (?, ?) is the first nationally representative household panel survey in Colombia. We focus on data on urban households, 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 **??**. On average, Table **??** shows about 31% 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 once likely to be really significant as 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 48% 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 (53%) than those above median wealth (43%). When breaking this by year of occurrence, 15% of households (14% among the relatively rich, 16% among the relatively poor) faced shocks in 2011, whereas the corresponding figure for 2012 was 22% (20% among the wealthier, 24% 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 **??**, revealing an average expenditure per month of about 100,000 Colombian pesos per person in the full sample (close to 30 US dollars), and a figure about 26% larger among the relatively wealthier households and 23% smaller among those below median wealth. Other key variables in our analysis are a rich set of controls for household and dwelling characteristics listed in Appendix Table **??** and described in Appendix Table **??**.

2.2 Persistence of bad shocks

A key idea of our empirical framework 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 **??** 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 11.8 percentage points more likely to face one again between 2010 and 2013, from a a baseline average incidence of adverse shocks of 45% over this period (with a standard deviation of 0.54). Thus, this correlation is quantitatively large: a bit over one-fourth of the mean and one-fifth of a 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, falling just .8 percentage points to 0.11.

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 ? (?) and recently improved upon by ? (?). 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 row of Column 2 follows ? (?) and presents this proportional constant for our estimation, finding a value of 13.55. That is, selection of unobservables would have to be almost 14 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 (?, ?).[4] Interestingly and in line with the results for observable selection the resulting estimate is again very stable, a 10.7 percentage point 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 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 simple regression of shocks between 2010 and 2013 on shocks preceding 2010 but where we control directly for the propensity score (?, ?). 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 **??** 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 response to the shock in terms of relevant mechanisms like food consumption, as by the time we survey them again in 2013, the potential endogenous 2012 shocks have been realized contaminating our measure. In this sense, we see both exercises as complementary with each providing a useful view.

Across all columns of Panel B we see again very consistent and highly significant esti-

[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.

mates, in this case just marginally smaller in magnitude to the longer-run effects, at almost 10 percentage points (the estimates range from 0.937 to 0.0997). 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 22% 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 50%. The stability of the coefficients across different estimation techniques again suggest 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, 2.35. While not as large as that of Panel A, it is still noteworthy that we would require more than twice the selection of unobservables relative to that of observables to explain away our result.

Table **??** presents our estimation of the propensity score for the regressions above for Panel A of Table **??** and a simple validation. In column 1 we model the probability of experiencing a shock before 2010 as a function of the set of household, dwelling, and community predetermined characteristics. These characteristics are highly jointly significant as revealed by the p-vale for the F-test of joint significance shown at the bottom of the table. Moreover, in column 2 we run 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) confirming 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 Panel B is relegated to Appendix Table **??**, simply for space convenience since, as explained, we have many more possible controls in this case. Again we find a propensity score where a number of covariates are important in predicting adverse shocks in 2011, and which effectively summarizes this influence in the simple validation exercise.

In summary, 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 10 percentage points implies a 50% 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 also suggests that certain types of households, in the brink of falling into a bad state of low assets, are particularly likely to respond to adverse shocks with inefficient strategies that lead to increased risk. To get a sense of whether such pattern appears in the data, we now examine the potential response of food consumption. Again, the approach is to use a simple propensity score matching estimators as in Table **??** to verify how the level of food consumption of households affected with negative shocks prior to 2010 compares relative to similarly vulnerable households with better luck.

Table **??** looks at the (inverse hyperbolic sine) of reported food expenditure as a function of shock incidence. The transformation just stabilizes variance in a manner similar as the log transformation but enables us to cope with negative values. Interestingly, most households do not sacrifice consumption except those located within the percentile 50-75 of our wealth index distribution. Households in this range as in the 25-75 range observe the largest drop in consumption, though in the latter case the coefficient is not statistically significant. Though just tentatively suggestive, the pattern does seem to suggest no significant drop in the extremes of the distribution an a fall in food consumption in the middle of the distribution.

2.4 Consequences of privation

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, our model suggests it is endogenously increasing the 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" (that is, 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. In this approach, control units are by definition in the normal level of consumption. Finally, we check the persistence of shocks for these two groups.

The results are in Table **??** 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 13 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.

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 ? (?). 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 Numerical Exercise

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 ? (?), 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 ? (?). 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 **??**). 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 **??**, differences in consumption levels can account for a difference in the probability of having an adverse shock of 9 percentage points. On the other hand, having a previous adverse shocks increases vulnerability in 10 percentage points according to Panel B of Table **??**. Using this information and assuming symmetry over these estimations, we calibrated the transition probabilities as in Figure **??** 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 **??** 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 third quartile. 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 **??**, 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.[5]

This implies that households that have assets below this intermediate region will never be able to accumulate enough assets to achieve the upper region. Therefore, they will be trapped forever at this low level of assets. Another implication is that a “rich” household could also end up in the poverty trap if it repeatedly experiences adverse shocks. Households in the poverty trap also face a higher vulnerability since their consumption tends to be below the threshold. Therefore, this model suggests 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 **??** 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.

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 responses. We showed that having a shock increases the likelihood of having a future adverse shock by about 10 to 11 percentage points depending on the timing we examine. We also showed that households in the third quantile of the wealth distribution decrease their consumption significantly by 0.9 percent when hit by the shock, relative to those that do not experience bad luck. This implies that the remaining households are able to smooth consumption relatively well with their assets. Thirdly, we show that persistence of bad shocks is 9 percentage points higher for households that decreased their consumption, compared to those that did not.

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. We assume the probability of having an adverse shock is decreasing in consumption and persistent, and we calibrate it using the estimates from the empirical section.

[5]The key assumption to obtain the poverty trap is the strong nonconcavity of the probability of facing an adverse shock. ? (?) 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.

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 below this level of assets will never be able to accumulate more assets because all the endowment is used to maintain higher levels of consumption to avoid an increased vulnerability. Since the empirical section found a significant decrease in consumption for households in the third quartile, this suggests that households in the first and second quartile are in a poverty trap. We also show that welfare losses are very large for the poorest households.

Table 1: Descriptive statistics, main variables
Colombian urban households

Variable	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
		Full sample			*Above median wealth index*			*Below median wealth index*	
Adverse shocks									
Prior to 2010	0.31	0.46	3053	0.29	0.45	1523	0.33	0.47	1530
Between 2010 and 2013	0.48	0.5	3053	0.43	0.5	1523	0.53	0.5	1530
In 2011	0.15	0.36	3053	0.14	0.35	1523	0.16	0.37	1530
In 2012	0.22	0.41	3053	0.2	0.4	1523	0.24	0.43	1530
Food expenditure									
Food expenditure per person 2010	100956.26	69545.08	3053	125020.22	78847.38	1523	77002.41	48110.76	1530

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	0.118***	0.110***	0.107***	0.110***
	(0.0199)	(0.0203)	(0.0200)	(0.0207)
Propensity Score				0.104
				(0.0806)
Observations	3048	3048	3014	3014
R^2	0.012	0.055		0.012
Dependent variable...				
Mean	.4783	.4783	.4760	.4760
Standard deviation	.4996	.4996	.4995	.4995
Unobservable selection		13.55		
Panel B: Dependent variable is Adverse Shocks in 2012				
Adverse Shocks in 2011	0.0991***	0.0937***	0.0939***	0.0937***
	(0.0256)	(0.0257)	(0.0278)	(0.0258)
Propensity Score				0.331*
				(0.174)
Constant	0.207***	0.449*		0.161***
	(0.00843)	(0.254)		(0.0255)
Observations	2859	2859	2853	2853
R^2	0.007	0.022		0.008
Dependent variable...				
Mean	0.22	0.22	0.22	0.22
Standard deviation	0.42	0.42	0.42	0.42
Unobservable selection		2.35		

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 and restricting to households in the same dwelling for more than two years. In column 4 we control for the propensity score underlying the corresponding matching estimator of column 1. Controls for regressions and propensity scores are: 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. Unobserved Selection is the degree of selection on unobservables relative to observables which would be necessary to explain away the main result.

Table 3: Propensity score estimation and validation
Probability of a shock prior to 2010

	(1)	(2)
Estimation method:	Probit	OLS
Dependent variable is Adverse Shocks prior to 2010		
Average education level 2010	-0.01	-0.00
	(0.01)	(0.00)
Education level of father 2010	0.00*	0.00
	(0.00)	(0.00)
Education level of mother 2010	-0.00*	-0.00
	(0.00)	(0.00)
Average can write & read	-0.02	-0.01
	(0.15)	(0.05)
Vulnerable location 2010	0.32***	0.14
	(0.06)	(0.08)
Floor material 2010	0.03	0.01
	(0.04)	(0.01)
Wall material 2010	-0.00	-0.00
	(0.04)	(0.01)
Electricity 2010	0.42	0.18
	(0.70)	(0.25)
Natural gas 2010	0.11	0.05
	(0.08)	(0.04)
Aqueduct 2010	-0.14	-0.04
	(0.27)	(0.09)
Sewer 2010	-0.17	-0.09
	(0.16)	(0.07)
Phone 2010	0.16**	0.06
	(0.06)	(0.04)
Garbage collection 2010	0.05	0.02
	(0.22)	(0.07)
Garbage elimination 2010	0.00	0.00
	(0.09)	(0.03)
Sanitary service 2010	-0.03	-0.02
	(0.06)	(0.02)
Water 2010	-0.12*	-0.03
	(0.07)	(0.02)
Cooking energy 2010	0.10*	0.04
	(0.05)	(0.03)
Exclusive kitchen 2010	0.02	0.01
	(0.11)	(0.04)
Room for food 2010	-0.05	-0.02
	(0.05)	(0.02)
Average precipitation	-0.00	-0.00
	(0.00)	(0.00)
Propensity score		-0.26
		(0.75)
Constant	-0.81	0.25
	(0.83)	(0.31)
Observations	2,723	2,723
R-squared		0.07
p-value joint significance	6.7×10^{-7}	0.9998

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions in column (1) and (2) have fixed effects at the municipal level. p-value joint significance is the p-value of joint significance of every variable, excluding the fixed effects and propensity score.

Table 4: Household food consumption response to adverse shocks

	(1)	(2)	(3)	(4)	(5)
Estimation Method:	Matching	Matching	Matching	Matching	Matching
Dependent variable is (the inverse hyperbolic sine of) reported food expenditure					
Adverse shocks prior to 2010	-0.06	-0.04	-0.09	-0.09*	-0.07
	(0.04)	(0.06)	(0.09)	(0.05)	(0.07)
Observations	2,723	650	654	653	603
Percentile	Full sample	0-25	25-50	50-75	75-100

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 **??**.

Table 5: 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	0.109***	0.0409	0.130***
	(0.0208)	(0.0334)	(0.0245)
Propensity Score	0.108	0.118	0.0556
	(0.0808)	(0.107)	(0.101)
Observations	2995	2311	2603
R^2	0.012	0.001	0.012
Dependent variable...			
Mean	.4774	.4478	.4713
Standard Deviation	.4995	.4973	.4992

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 **??**. 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.

Figure 1: Probability of a Bad Shock

Figure 2: Optimal policy for consumption

Figure 3: Optimal policy rule for assets

Figure 4: Optimal Value Function

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, government bonds, 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.
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 2010	Average education level of the head of the household and spouse.
Education level of father 2010	Average education level of the fathers of: head of the household and spouse.

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

Variable name	Description
Education level of mother 2010	Average education level of the mothers of: of: head of the household and spouse.
Average literacy 2010	Average of dummy variable for knowing to read and write, household and spouse.
Vulnerable location 2010	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 2010	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; 5 if floor is made of dust; 6 if floor is made of other.
Wall material 2010	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.
Electricity 2010	Binary variable. Equals 1 if the household has electricity service
Natural gas 2010	Binary variable. Equals 1 if the household has natural gas service connected to the public net.
Aqueduct 2010	Binary variable. Equals 1 if the household has aqueduct service.
Sewage 2010	Binary variable. Equals 1 if the household has sewage service.
Phone 2010	Binary variable. Equals 1 if the household has phone services.
Garbage collection 2010	Binary variable. Equals 1 if the household has garbage collection services.
Garbage elimination 2010	Categorical variable which equals: 1 if garbage is picked by cleaning services; 2 if garbage is buried; 3 if garbage is burned; 4 if garbage is thrown in the yard or any property (plot, *zanja* or *baldio*); 5 if garbage is thrown in a river, pipes, or in a pong; 6 other.
Sanitary service 2010	Categorical variable which equals: 1 if the household has a toilet connected to the sewage; 2 if the toilet is connected to a septic tank; 3 if the toilet has no connection; 4 if the household has a latrine; 5 if the household has a *bajamar*; 6 it the household does not have sanitary services.
Water 2010	Categorical variable which equals: 1 if water is collected from public aqueduct; 2 if water is collected from communal or village aqueduct; 3 if water is collected from a well with pump; 4 if water is collected from rain; 5 if water is collected from a river; 6 if water is collected from a public pond (pila publica); 7 water is collected from tanker truck; 8 if water is collected from bottles etc.

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

Variable name	Description
Cooking energy 2010	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.
Exclusive kitchen 2010	Binary variable. Equals 1 if household prepares food in area of exclusive use.
Room for food 2010	Categorical variable which equals: 1 if there is a room used exclusively for cooking; 2 if the room used for cooking is a bedroom; 3 if the room used for cooking is the living room and has dishwasher; 4 if the room used for cooking is the living room and does not have dishwasher; 5 if the place for cooking is a room outside; 6 there is no specific place for cooking.
Average precipitation	Average of monthly precipitation next to the closets IDEAM station for the years 1980-2009.

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

Variable	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
		Full sample			*Above median wealth index*			*Below median wealth index*	
Education									
Average education level 2010	4.44	2.13	3053	5.17	2.42	1523	3.71	1.49	1530
Average literacy 2010	0.95	0.19	3053	0.98	0.12	1523	0.92	0.23	1530
Vulnerable location 2010	0.29	0.45	3053	0.29	0.45	1523	0.29	0.45	1530
Floor material 2010									
Carpet	0.06	0.24	3053	0.09	0.29	1523	0.03	0.17	1530
Ceramic tiles	0.57	0.49	3053	0.75	0.43	1523	0.39	0.49	1530
Cement	0.32	0.47	3053	0.14	0.35	1523	0.5	0.5	1530
Wood in bad condition	0.02	0.13	3053	0.01	0.1	1523	0.02	0.15	1530
Dust	0.03	0.18	3053	0.01	0.07	1523	0.06	0.24	1530
Other material	0	0.03	3053	0	0	1523	0	0.04	1530
Walls material 2010									
Bricks	0.93	0.25	3053	0.97	0.16	1523	0.89	0.31	1530
tapia pisada	0.02	0.14	3053	0.02	0.13	1523	0.02	0.15	1530
Bahareque	0.03	0.17	3053	0.01	0.08	1523	0.05	0.22	1530
Prefabricated material	0	0.07	3053	0	0.04	1523	0.01	0.09	1530
Wood in bad condition	0.01	0.1	3053	0	0.04	1523	0.02	0.14	1530
Bamboo	0	0.03	3053	0	0	1523	0	0.04	1530
Zin, cans or any waste	0	0.05	3053	0	0.03	1523	0	0.06	1530
Public Services 2010									
Natural gas	0.70	0.46	3053	0.79	0.41	1523	0.62	0.49	1530
Aqueduct	0.97	0.18	3053	0.99	0.1	1523	0.94	0.23	1530
Sewage	0.92	0.26	3053	0.98	0.14	1523	0.87	0.34	1530
Phone	0.57	0.5	3053	0.79	0.41	1523	0.34	0.47	1530
Garbage collection	0.98	0.13	3053	0.99	0.09	1523	0.97	0.16	1530
Garbage Elimination 2010									
Picked by clean services	0.98	0.15	3053	0.99	0.1	1523	0.97	0.18	1530
Buried	0	0.06	3053	0	0.06	1523	0	0.06	1530
Burned	0.01	0.11	3053	0	0.04	1523	0.02	0.15	1530
Thrown in yard	0	0.05	3053	0	0.06	1523	0	0.05	1530
Thrown in a river	0	0.04	3053	0	0.04	1523	0	0.04	1530
Other	0	0.04	3053	0	0.03	1523	0	0.06	1530
Sanitary Service 2010									
Toilet connected to sewage	0.91	0.29	3053	0.98	0.15	1523	0.84	0.36	1530
Toilet connected to septic tank	0.07	0.26	3053	0.02	0.14	1523	0.12	0.33	1530
Toilet without connection	0	0.04	3053	0	0	1523	0	0.06	1530
Latrine	0.01	0.09	3053	0	0	1523	0.02	0.12	1530
Bajamar	0	0.02	3053	0	0	1523	0	0.03	1530
No sanitary services	0.01	0.09	3053	0	0.04	1523	0.02	0.12	1530
Water 2010									
Public aqueduct	0.91	0.28	3053	0.97	0.17	1523	0.85	0.35	1530
Communal or village aqueduct	0.05	0.21	3053	0.02	0.12	1523	0.08	0.26	1530
Well with a pump	0.01	0.11	3053	0	0.07	1523	0.02	0.14	1530
Well without a pump	0.01	0.09	3053	0.01	0.08	1523	0.01	0.1	1530
Rain	0.01	0.11	3053	0	0.03	1523	0.02	0.15	1530
River	0	0.02	3053	0	0	1523	0	0.03	1530
Public pond	0	0.02	3053	0	0.03	1523	0	0	1530
Tanker truck	0	0.07	3053	0	0.03	1523	0.01	0.09	1530
Bottles etc.	0	0.07	3053	0	0.05	1523	0.01	0.08	1530
Cooking energy 2010									
Electricity	0.05	0.21	3053	0.05	0.22	1523	0.04	0.19	1530
Natural gas	0.67	0.47	3053	0.75	0.43	1523	0.59	0.49	1530
Propane gas	0.26	0.44	3053	0.19	0.4	1523	0.32	0.47	1530
Kerosene, oil, petroleum	0	0.03	3053	0	0	1523	0	0.04	1530
Wood	0.02	0.15	3053	0	0.07	1523	0.04	0.2	1530
Mineral Carbon	0	0.02	3053	0	0	1523	0	0.03	1530
Kitchen or Cooking place 2010									
Exclusive Kitchen	0.94	0.24	3053	0.97	0.16	1523	0.91	0.29	1530
Room for cooking	0.94	0.23	3053	0.98	0.13	1523	0.9	0.3	1530
Room for cooking and sleeping	0.02	0.13	3053	0	0.07	1523	0.03	0.17	1530
Cook in livingroom with dishwasher	0.01	0.12	3053	0.01	0.09	1523	0.02	0.13	1530
Cook in livingroom without dishwasher	0.01	0.11	3053	0	0.04	1523	0.02	0.15	1530
Cook outside	0.01	0.12	3053	0	0.05	1523	0.03	0.16	1530
No place for cooking	0	0	3053	0	0	1523	0	0	1530
Average precipitation	73.64	50.15	3053	71.06	52.02	1523	76.22	48.1	1530

Table A-3: Propensity and validation Adverse shock persistence in the short run

Estimation method:	(1) Probit	(2) OLS
Dependent variable is Adverse Shocks in 2011		
Basic School 2010	-0.0185	0.00432
	(0.137)	(0.0313)
Secondary School 2010	0.0303	-0.00269
	(0.136)	(0.0313)
Technician without degree 2010	0.0111	0.00292
	(0.282)	(0.0632)
Technician with degree 2010	-0.00995	0.00400
	(0.186)	(0.0418)
Technician2 without degree2010	0.289	-0.0300
	(0.398)	(0.108)
Technician2 with degree 2010	0.254	-0.0307
	(0.223)	(0.0735)
University without degree 2010	0.165	-0.0169
	(0.223)	(0.0600)
University with degree 2010	-0.0774	0.00889
	(0.205)	(0.0455)
Postgraduate with degree 2010	0.322	-0.0341
	(0.283)	(0.0853)
Income 2010	-3.00e-07**	3.20e-08
	(1.22e-07)	(5.16e-08)
Number of Stereos 2010	-0.0751	0.0111
	(0.0592)	(0.0203)
Owners of dwelling 2010	0.0108	-0.00159
	(0.0246)	(0.00593)
Number of people 2010	0.0118	-0.00172
	(0.0161)	(0.00458)
Debts 2010	0.184***	-0.0244
	(0.0609)	(0.0386)
Familias en acción 2010	-0.0852	0.0121
	(0.0768)	(0.0255)
Houses 2010	-0.0944	0.00992
	(0.140)	(0.0336)
Refrigerator 2010	-0.0244	0.00374
	(0.0874)	(0.0202)
Washing machine 2010	0.228***	-0.0303
	(0.0689)	(0.0483)
Blender 2010	0.0481	-0.00595
	(0.0902)	(0.0219)
Oven 2010	-0.0985	0.0134
	(0.0783)	(0.0263)
Microwave 2010	0.00879	-0.00356
	(0.0916)	(0.0200)
Spout 2010	-0.154**	0.0202
	(0.0755)	(0.0366)
Heater 2010	-0.0160	0.00207
	(0.0936)	(0.0196)
Shower 2010	0.0227	-0.00184
	(0.0770)	(0.0172)
Air conditioner 2010	-0.0733	0.00933
	(0.0619)	(0.0177)
Government bonds 2010	0.214	-0.0303
	(0.406)	(0.0941)
Av precipitation	9.50e-05	-4.62e-06
	(0.000567)	(0.000127)
Constant	-1.252	-0.0612
	(0.834)	(0.199)
Propensity Score		1.601*
		(0.900)
Observations	2853	2853
R-squared		0.017
p-value joint significance	.025	0.9998

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Regressions in column (1) and (2) have fixed effects at the municipal level. p-value joint significance is the p-value of joint significance of every variable, excluding the fixed effects and propensity score.