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The Demand for Energy-Using Assets among the World's Rising Middle Classes†

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We study household decisions to acquire energy-using assets in the presence of rising incomes. We develop a theoretical framework to characterize the effect of income growth on asset purchases when consumers face credit constraints. We use large and plausibly exogenous shocks to household income generated by the conditional-cash-transfer program in Mexico, Oportunidades, to show that asset acquisition is nonlinear, depends, as predicted in the presence of credit constraints, on the pace of income growth, and both effects are economically large among beneficiaries. Our results may help explain important worldwide trends in the relationship between energy use and income growth. (*JEL* D12, I32, I38, O12, O13, Q47)

Energy is a fundamental input to modern life. Without access to commercial energy sources, such as gasoline, natural gas, and electricity, people could not drive vehicles, refrigerate food and medicine, air condition buildings, watch television, easily operate farming equipment, or participate in many other aspects of modern life. Despite this, an estimated 1.3 billion people live without electricity in their homes, and even among those who have access, many do not own basic assets such as refrigerators, motorized transport, or washing machines. In fact, Table 1 demonstrates the low penetration of several key energy-using assets for over 4 billion people living in the developing world, especially when compared to high-income countries such as the United States. However, this situation is rapidly changing as incomes rise from economic growth and as massive poverty alleviation programs continue to expand.

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Table 1—Energy-Using Asset Ownership in the Developing World

	Electricity access (percent of population)	Refrigerators (share of households)	Cars (per 1,000 people)	Population (millions)
Brazil	98.7	0.93	209	197
China	99.7	0.69	58	1,344
India	75.0	0.13	18	1,221
Indonesia	73.0	0.17	60	245
Mexico	97.9	0.83	275	119
Sub-Saharan Africa	32.5	0.11	28	886
Total	70.8	0.38	53	4,012
United States	100.0	0.99	797	312

Notes: Population numbers are from 2011. Data on electricity access and cars are from 2008–2010, except Mexico electricity access is from 2012. Refrigerator shares come from a variety of country-specific nationally representative surveys for the following years: Brazil (2009); China (2010); India (2007–2008); Indonesia (2004); Mexico (2008); sub-Saharan Africa: aggregated country-level surveys (2006); United States (2011).

Sources: National Bureau of Statistics (2011); United States Census Bureau (2013); Wolfram, Shelef, and Gertler (2012); World Bank (2011).

We analyze household decisions to acquire energy-using assets, focusing on the role of rising incomes in the developing world where the vast majority of the growth in energy use is expected (Energy Information Administration (EIA) 2013). Importantly, and in contrast to previous literature, we allow for the presence of credit constraints, which we show have significant implications for the timing of asset acquisitions and, consequently, for the demand for energy. This is important as credit is severely constrained throughout much of the developing world, especially for the poor and near poor (Karlan and Morduch 2010).[1] In rural Mexico, the site of our empirical application, credit opportunities are very limited as only 1 percent of communities have a formal credit institution and only 3 percent of households report having active loans, almost all of which are small informal loans from friends and relatives (Gertler, Martinez, and Rubio-Codina 2012).

We are interested in acquisition of energy-using assets for two reasons. First, they are important drivers of health and human development (World Bank 2008). Air conditioning lowers heat-related mortality (Barreca et al. forthcoming) and refrigeration improves child health outcomes (Wolfe and Behrman 1982). There are also established causal linkages between access to electricity and female labor force participation (Dinkelman 2011), housing values, and the UN Human Development Index (Lipscomb, Mobarak, and Barham 2013). While there is some work on the acquisition of energy-using assets in the developed world,[2] ours is the first to analyze the acquisition of these goods in the developing world.[3]

[1] See also http://datatopics.worldbank.org/financialinclusion/.

[2] See, for example, recent contributions on heating systems by Davis and Kilian (2011) and automobiles by Busse, Knittel, and Zettelmeyer (2013).

[3] In some countries, there are large upfront prices for an electricity connection. In Kenya, for example, the cost of connecting to the electricity grid is around $400, about one-third of the average annual income in the country. By contrast, other countries, such as South Africa, have subsidized the cost of the connection entirely. Connection costs in Mexico are on the low end of this range, though not zero. Our model highlights the potential role of income growth and credit markets in increasing connections, another asset households acquire, in places like Kenya.

Second, the growth in energy demand driven by rising energy use among first-time purchasers of household appliances and other energy-using assets is likely to have important implications for macro-level trends in energy use. In terms of scale, if, for example, one-half of the households in India who do not own refrigerators were to buy one, annual *nationwide* electricity demand across all sectors—residential, commercial, and industrial—would rise by over 10 percent.[4] Rapid first-time asset acquisition is already taking place in some parts of the world. For instance, vehicle ownership in urban China has risen at almost 40 percent *per year* between 2000 and 2010, helping fuel China's rapid growth in oil consumption (National Bureau of Statistics 2001, 2011).

Understanding the likely growth in demand for energy is critical for several reasons. First, investments in energy infrastructure require long lead times, and most governments and energy companies base their investment decisions on demand projections. Incorrect forecasts can lead to local energy shortages that affect both productivity and welfare (Allcott, Collard-Wexler, and O'Connell 2016). On a global scale, faster than anticipated growth in energy demand can lead to significant increases in energy prices. Second, energy use is a key contributor to climate change as energy-related emissions account for three-quarters of worldwide anthropogenic greenhouse gas emissions.[5] Forecasting the likely path of greenhouse gas emissions is essential to understanding the range of possible effects of climate change. Furthermore, expected country-level emissions are critical inputs to any plans to mitigate climate change, including an international climate agreement.

We demonstrate elsewhere that existing energy forecasts do not appear to account sufficiently for the nonlinear relationship between energy and income (Wolfram, Shelef, and Gertler 2012). This paper begins by documenting motivating evidence of a nonlinear relationship between income and both asset ownership and energy use at the individual, municipality, and country levels. Since households do not consume energy directly but rather through appliances, this suggests that there is an empirical regularity to be explained with micro evidence on appliance purchases. We next develop a simple theoretical model that suggests a nonlinear Engel curve, meaning that as income goes up from initially very low levels, credit-constrained households do not become more likely to purchase an energy-using asset. Above a certain threshold, however, increases in income are much more likely to lead to asset purchases, suggesting a nonlinear relationship between income and asset acquisition. Our theoretical model also predicts that the speed at which credit-constrained households' incomes grow will affect their asset acquisitions. The model further predicts a positive interaction between the rate of income growth and income levels, so the impact of rapid income growth is accentuated at higher income levels.

[4] In 2007, 86.5 percent of Indian households did not own refrigerators. Extrapolating growth in acquisitions, by 2011, an estimated 84 percent of households did not own refrigerators (Wolfram, Shelef, and Gertler 2012). Population in 2011 was 1.210 billion. Assuming 5 people per household, 205 million households lack refrigerators. Assuming refrigerators use 1,000 kilowatt hours per year (though new models can be more efficient, this would be a relatively efficient used refrigerator) acquisition by one-half of the households would be 101,648 gigawatt hours per year, which is 10 percent of generation of electricity of 985,443 gigawatt hours in 2011 (EIA 2011). Using generation as the denominator understates the potential impact since line losses mean that more electricity needs to be generated than consumed.

[5] See, for example, http://www.epa.gov/climatechange/science/indicators/ghg/global-ghg-emissions.html.

We next use large and plausibly exogenous shocks to household income generated by the conditional cash transfer program in Mexico, Oportunidades, to empirically show that the nonlinear relationship between income and asset acquisition is important among low-income Mexican households. We also find strong empirical support for both of the predictions on the growth rate of income, providing further validation for the importance of credit constraints and the implied nonlinear relationship between income growth and asset acquisition.

The next section describes motivating evidence on the nonlinear relationship between income and both asset ownership and energy use drawn from several different locations and levels of aggregation. Section II presents a simple two-period model of asset acquisition in the presence of borrowing constraints and varying rates of income growth. Section III describes the Oportunidades program, which we use to test the predictions of our model. Section IV describes our empirical approach. We present results on asset acquisition by Oportunidades households in Section V. Finally, Section VI concludes.

I. Motivating Facts

A. *Income and Asset Ownership*

We begin by documenting an S-shaped relationship between income and durable asset ownership.[6] Figure 1 uses household data from several of the most populous developing countries to plot the share of households that own refrigerators against household expenditures per capita.[7] The dashed lines show the density of households by expenditure level. The top panels depict regions that have experienced recent income growth among the poor, largely driven by poverty alleviation programs in Mexico and Brazil, and economic growth in urban China. As a result, a substantial share of households in these regions has already moved through the income level associated with the inflection point in refrigerator ownership. The bottom row, however, shows that there are still significant populations poised to buy refrigerators in India, Indonesia, and rural China, which together represent more than 2 billion people.

Figure 2 depicts changes in refrigerator ownership over time showing that the nonlinear relationship is also reflected in adoption associated with income growth. The graph shows changes in the share of Mexican households owning a refrigerator by real household consumption level. The gray line reflects changes between 1992 and 1996. At that point, most of the growth in refrigerator ownership was concentrated

[6] Several existing papers have also noted the S-shaped relationship between income and durable asset purchase including Kopits and Cropper (2005); Dargay, Dermot, and Sommer (2007); and Letschert and McNeil (2007). While the existing literature documents the existence of S-shaped cross-sectional correlations, we provide a model to explain it, and show that the relationship is indeed causal.

[7] This paper focuses on refrigerators in part because they are easy to measure consistently across households. Other assets, such as hot water heaters, may range from an outdoor container angled to catch daytime sun to a commercially powered on-demand or stand-alone unit. Refrigerators also represent a sizable share of residential electricity consumption, totaling one-third of total household electricity consumption in Mexico and China, two countries for which we have data (Zhou et al. 2011 and personal communication; National Bureau of Statistics 2011; Johnson et al. 2009). Finally, as households purchase refrigerators, they become consumers of refrigerated products, and considerable energy is used to keep food chilled while it is manufactured, transported, warehoused, and finally sold retail. Estimates suggest that 15 percent of global energy is devoted to the "cold chain" (Twilley 2014), which also accounts for one-third of global emissions of hydrofluorocarbons (HFCs), a potent greenhouse gas (PR Newswire 2014).

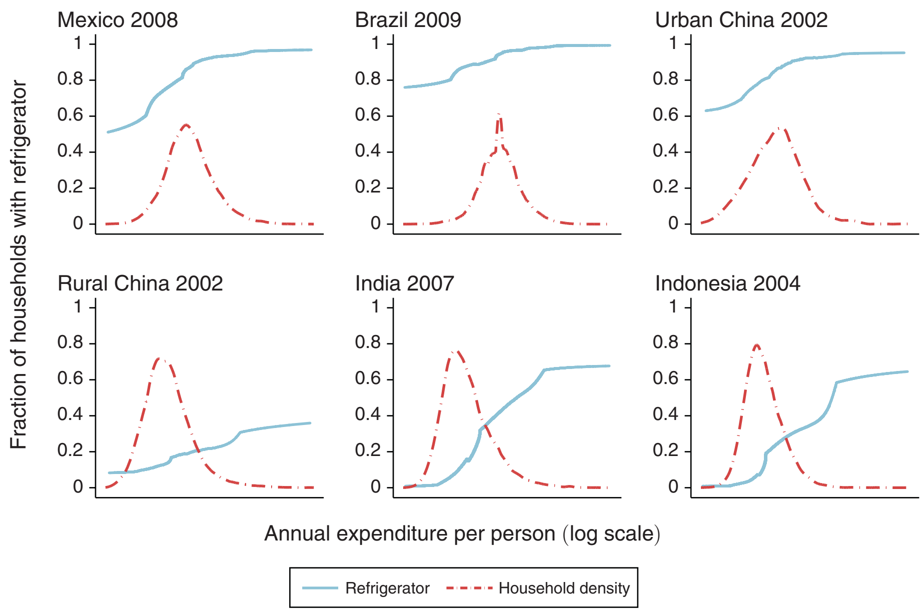

Figure 1. Refrigerator Ownership and Household Expenditure Level

Notes: Annual expenditure and income per person calculations divides household expenditure and income by the number of adult equivalents in the household, where each household member under 12 years old is treated as half an adult. Frequency weights are used for all surveys other than China, which do not report weights. Brazil uses annual income per person instead of expenditure.

Sources: Mexico, 2008: Encuesta Nacional de Ingresos y Gastos de los Hogares; Brazil, 2009: National Household Sample Survey PNAD; China, 2002: Chinese Household Income Project; India, 2008: National Sample Survey; Indonesia, 2004: National Socio-Economic Survey (SUSENAS).

in the middle consumption levels, with lower growth for both the wealthiest and the poorest households. The black line depicts changes between 2004 and 2008. By this point, new acquisitions are most prevalent among households with the lowest consumption, which is consistent with a general movement of the population through an S-curve. In other words, in the mid-1990s, incomes among the poorest Mexicans were still too low to support refrigerator acquisitions. But as incomes grew and real refrigerator prices fell, the mass of refrigerator purchasers shifted toward poor households and the plot suggests that Mexico has developed such that only the top half of the S-curve is now relevant.

B. *Income and Energy Use*

One concern is that a nonlinear relationship between income and the purchase of a single asset may disappear when data are aggregated across the purchase of many durable assets. Specifically, even if there is a nonlinear relationship between refrigerators and income, and even if refrigerators are representative of other energy-consuming assets, it is possible that a series of nonlinear relationships at different inflection points may manifest as a linear relationship when aggregated across assets. This could translate into a linear relationship between income and energy demand.

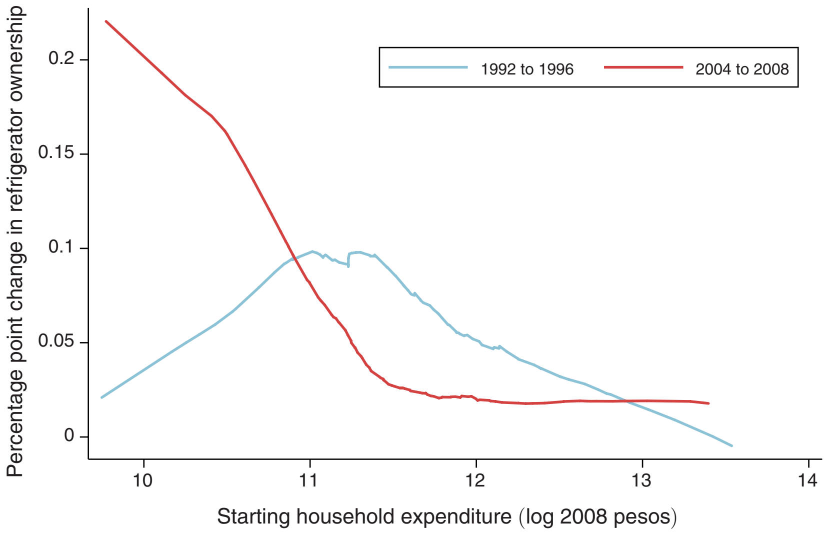

FIGURE 2. CHANGE IN REFRIGERATOR OWNERSHIP BY HOUSEHOLD EXPENDITURE LEVEL

Notes: The gray line plots the change in the share of households owning a refrigerator between 1992 and 1996 by 1992 expenditures per adult equivalent. The black line plots the change in that share between 2004 and 2008 by 2004 expenditures per adult equivalent. Both lines reflect smoothed values for a locally weighted LOWESS regression excluding the top 1 percent of households by expenditures per adult equivalent. We form a pseudo panel by calculating, at each percentile of the expenditure distribution, the mean household expenditure and change in refrigerator ownership across the base and end years. Expenditure per adult equivalent is deflated by the urban and rural Mexican Consumer Price Indices, though these may be imprecise in the mid-1990s given the currency crisis and they do not necessarily capture changes in refrigerator prices over the time period. Heterogeneous income growth, such as that received by low-income households between 2004 and 2008 due to Oportunidades, will lead to heterogeneous acquisition. Figure 2 reflects household-level, repeated cross-section data from a nationally representative sample.

Sources: Encuesta Nacional de Ingresos y Gastos de los Hogares 1992, 1996, 2004, and 2008.

Figure 3 provides additional support for a nonlinear relationship between income and energy. Panel A of Figure 3 suggests that overall linearity is not the case among Oportunidades households. It plots the log of energy (gas plus electricity) expenditures against the log of total household consumption in 2007. The figure shows an S-shape with a nontrivial share of households below the total consumption level at which the slope of the relationship increases.[8]

The analysis so far applies only to Oportunidades households, which come from the bottom quintile of the income distribution, only reflects the residential sector, and only represents one year, 2007. Panel B of Figure 3 reflects the income-energy use relationship for Mexico as a whole using municipality-level data for 2000–2010.

[8] The relationship in panel A of Figure 3 does not control for differences across households. We also regressed the log of energy expenditures on the log of total consumption and fully saturated the model with village fixed effects and household-level controls. For households below the twenty-fifth percentile in total consumption the estimated coefficient on log total consumption was -0.013 (standard error $=$ 0.092) while the estimated coefficient for households above the twenty-fifth percentile was 0.214 (standard error $=$ 0.036). The coefficients are significantly different from one another at the 2 percent level and are consistent with the first part of an S-shaped relationship between energy use and income: i.e., a flat relationship at low-income levels and positive at higher levels.

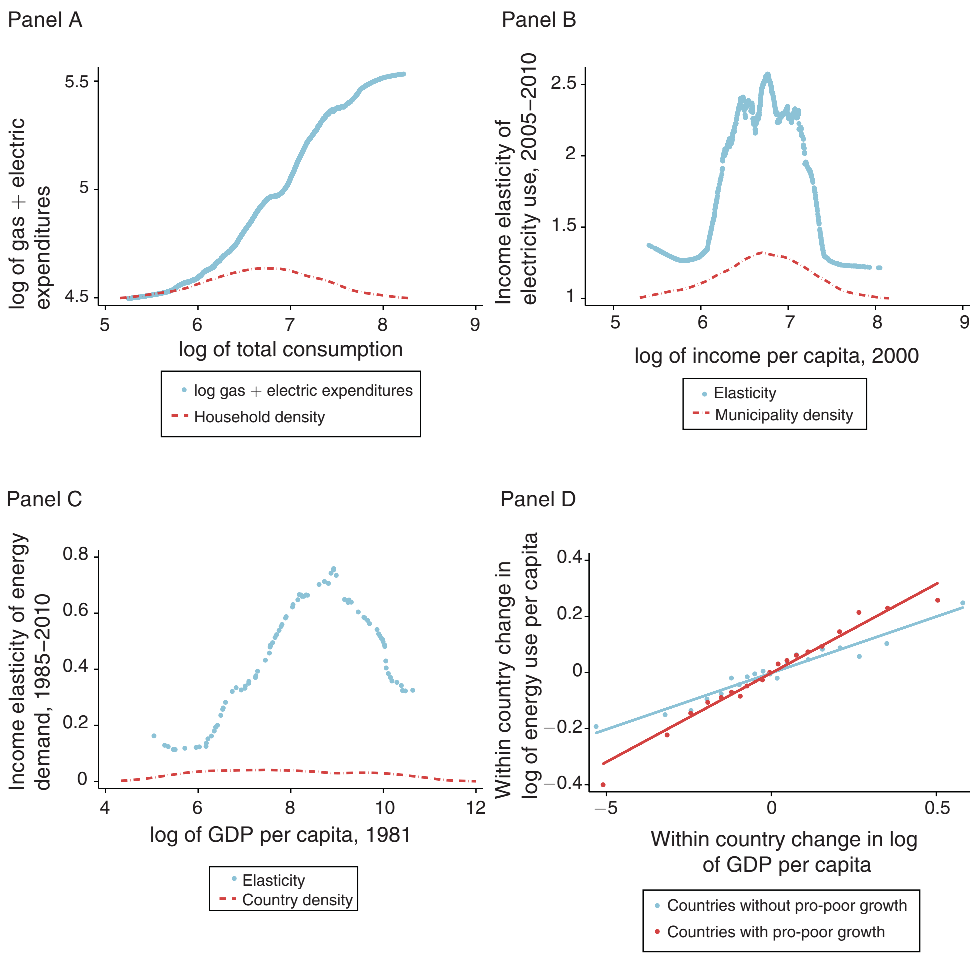

Figure 3. Examples of Nonlinear Relationship between Income and Energy Use

Notes: In panels A to C, the dark, solid line or points plot the smoothed values from a locally weighted LOWESS regression and the dashed line plots the kernel density estimates of the observations. Panel A reflects household-level data. Panel B reflects municipality-level data. In panel B, the income elasticity is estimated for each municipality as the percent change in energy expenditures between 2005 and 2010 divided by the percent change in income. Panel C reflects country-level data and includes countries that reported data consistently from 1980 to 2010 and excluded 15 major oil producers. Requiring data since 1980 excludes the former Soviet Republic and Eastern bloc countries. Appliance ownership rates are very high in those countries given their incomes and weakly correlated with income. Panel D reflects within country changes and uses energy consumption per capita and GDP per capita from 1980–2010 demeaned at the country level. Countries are categorized as having pro-poor growth if the decrease in the reported Gini coefficient exceeds the median. We include countries for which both energy use and multiple Gini measures are available. Lines are ordinary least squares (OLS) regressions.

Sources: Panel A, 2007 Oportunidades Evaluation Survey (ENCEL). Panel B, World Bank's Poverty and Gender Unit, Latin America and Caribbean region, which uses inputs from the Household Income and Expenditure Survey (ENIGH) of 1992, 2000, 2005, and 2010, and from the population census of 1990, 2000, 2005, and 2010, and employs the small-area estimation methodology proposed by Elbers, Lanjouw, and Lanjouw (2003). Electricity data are from Instituto Nacional de Estadistica, Geografia e Informatica (INEGI) at: http://www3.inegi.org.mx/sistemas/biinegi/. Panels C and D, World Bank's World Development Indicators series (http://databank.worldbank.org/data/views/variableSelection/selectvariables.aspx?source=world-development-indicators).

Panel B plots the smoothed relationship between each municipality's income elasticity of demand for electricity between 2005 and 2010 against baseline per capita income in 2000. The horizontal axis reflects the log of average per capita municipal income in 2000 and the vertical axis reflects the municipal income elasticity of per capita electricity consumption estimated between 2005 and 2010.[9]

If there is an S-shaped relationship between income and energy use that is fixed over time, then as incomes rise, the income elasticity at a point on the income distribution will equal the slope of the S-curve at that point. The inverse-U relationship between the income elasticity of electricity consumption and the income of the municipality in panel B is consistent with the S-shaped relationship: for municipalities with low average incomes, the income elasticity is low but rises in the middle part of the income distribution before falling again at the high points.

We obtain similar patterns to Mexican municipalities using data across countries. Panel C plots the income elasticity of per capita energy consumption estimated between 1985 and 2010 versus the log of average per capita income in 1981. Again, we see an inverse-U relationship, consistent with the S-curve.[10]

To demonstrate that cross-household differences could be driving country-level trends, panel D of Figure 3 plots log per capita energy consumption against log per capita GDP, both demeaned at the country level. We include the same set of countries and use the same data as in panel C for 1980–2010. We separate countries into two equally sized bins according to the change in the reported Gini coefficient.[11] Countries with larger reductions in their Gini coefficients, suggesting more of the growth has gone to households on the lower end of the income distribution, will have a larger share of households passing through the first inflection point on the S-curve. Panel D of Figure 3 suggests that increases in energy use for a given increase in per capita GDP have been 50 percent higher in countries with pro-poor growth (black) compared to countries with more regressive growth (gray).

In sum, the patterns depicted in this section are consistent with a nonlinear relationship between income and energy consumption both at the household and aggregate levels and suggest that further investigation of the relationship between appliance purchases, which drive energy consumption, and income is warranted.

II. Theoretical Model

This section presents a simple model that elucidates the relationship between income and the purchase of energy-using assets in the presence of credit constraints. In their influential paper, Dubin and McFadden (1984) emphasize that energy consumption depends not only on the usual utility-maximization problem as a function of income and energy prices, but also on the household's current appliance holdings. A number of subsequent papers have analyzed appliance acquisitions, however, few

[9] We plot the income elasticities against 2000 income instead of 2005 income so that the base year for the elasticity calculation is not the same as the scale for the horizontal axis. If it were the same, quicker mean reversion in income than electricity consumption could generate an inverse-U relationship mechanically.

[10] As in panel B, we plot the elasticities against 1981 income so that the base year for the elasticity calculation is different from the year reflected on the horizontal axis.

[11] Demeaning the data controls for the level of inequality, level of energy use, and other fixed country-specific attributes. Results are very similar if we use alternate definitions of pro-poor growth in place of the change in the Gini coefficient, though Gini is reported most consistently.

researchers have analyzed the intertemporal dynamics that may influence these decisions. In fact, most researchers make assumptions that preclude intertemporal considerations, such as perfectly efficient capital markets.[12] While such assumptions may or may not be appropriate in the developed world, it is clear that capital constraints are significant among the poor in the developing world.[13] In Section IIA we lay out notation and assumptions. Many of the assumptions are for expositional clarity and are not necessary to generate the model predictions. In online Appendix A, we relax several assumptions and demonstrate the results hold more generally. In Section IIB we generate a series of results that allow us to derive the empirically testable predictions in Section IIC.

A. *Model Setup*

We model decisions by an individual i who consumes two goods: a continuous nondurable good that gives per-period utility $u(\cdot)$, and a lumpy durable asset that gives static per-period utility R if owned. We normalize the price of the nondurable to 1, and denote the price of the durable as P.

Consider a simple two-period model without interest or discounting. We denote consumer i's period 1 income as Y_1 and period 2 income as Y_2. Define $\bar{Y} = (Y_1 + Y_2)/2$ the average per period income and $a = Y_2/\bar{Y}$ a measure of income growth. We assume that income is weakly increasing so that $a \in [1,2]$[14] and that Y and R are uncorrelated and that the consumer has no uncertainty over Y_2. For expositional clarity, we assume that the price of the good, P, is high enough relative to income levels and growth that any individual who buys in period 2 optimally saves a bit in period 1: $P > 2\bar{Y}(a - 1)$. That is, the difference in income between the two periods is less than P. We make two assumptions on the shape of the consumer's utility function: decreasing marginal utility, i.e., that $u(\cdot)$ has $u'(\cdot) > 0$, $u''(\cdot) < 0$, and an additional assumption on the utility function that is implied by either decreasing risk aversion, prudence, or precautionary savings. See online Appendix A for further details.

B. *Results*

As a benchmark, absent credit constraints the purchase of the asset does not depend on the time path of income. The household either buys in period 1, or not. Without credit constraints and if not purchasing, the optimal consumption of the

[12] For example, Dubin and McFadden (1984) and, more recently, Bento et al. (2009), assume a perfectly competitive rental market for durables. This could exist in the presence of efficient capital markets and an efficient resale market. In recent work, Rapson (2014) and Schiraldi (2011) model dynamic considerations focusing on, respectively, consumer expectations about future energy (i.e., usage) prices and heterogeneous consumer transaction costs. No papers, of which we are aware, explicitly model credit constraints or analyze durable good acquisition in the developing world.

[13] Liquidity constraints and poverty has been explored in Banerjee and Newman (1993); Aghion and Bolton (1997); Lindh and Ohlsson (1998); Lloyd-Ellis and Bernhardt (2000); Banerjee (2004); and de Mel, McKenzie, and Woodruff (2008) among others and are surveyed in Karlan and Morduch (2010). There are also studies looking at the novel institutions developed to partially overcome credit constraints including: ROSCAs (Besley, Coate, and Loury 1993) and microfinance (Hossian 1988). None of these intuitions address household durables, either in intent or scale.

[14] Without this assumption, credit constraints are nonbinding.

household is $\bar{Y}$ in each period leading to utility $u(\bar{Y})$ in each period. The household buys if and only if (we drop the subscripts i from this point on to avoid clutter):

$$u(\bar{Y}) - u\left(\bar{Y} - \frac{P}{2}\right) \leq R. \tag{1}$$

Decreasing marginal utility implies that $u\left(\bar{Y} - \frac{P}{2}\right)$ increases faster than $u(\bar{Y})$ in income, meaning that acquisition is increasing in income.

With credit constraints, we consider the three possible cases: the consumer buys in period 1, buys in period 2, or never buys. We'll define the trade-offs involved in each of these choices and plot the implied indifference surfaces to show how the propensity to purchase changes with income.

Case 1 (Buy in Period 1).—The household is indifferent between buying in period 1 and not buying if and only if:

$$\frac{u(Y_1) - u(Y_1 - P)}{2} = R. \tag{2}$$

Define the surface B as all (Y_1, Y_2, R) triplets that satisfy this equality. Households above this surface strictly prefer to buy in period 1 than to not acquire.

Case 2 (Wait and Buy in Period 2).—The household is indifferent between saving and buying in period 2 and not buying if and only if:

$$u(Y_1) + u(Y_2) - 2u\left(\bar{Y} - \frac{P}{2}\right) = R. \tag{3}$$

Define the surface W as all (Y_1, Y_2, R) triplets that satisfy this equality. Households with R greater than this strictly prefer to buy in period 2 than to not acquire.

This comparison provides intuition as to how credit constraints affect the acquisition decision. Decreasing marginal utility implies that consumers gain from equating consumption across periods. An unconstrained household can buy in period 1 and equate consumption in each period through borrowing. Credit constrained households cannot. They can create or magnify inequality in consumption between periods and buy immediately, or give up some of the benefit of the asset by delaying the purchase, but gain by being able to equate consumption across periods by saving. Higher income in any period leads savers to purchase more, but first period buyers respond only to their first period income, because they cannot access second period income to purchase in the first period (Lemma 1 below). Thus, an increase in cumulative income increases acquisition through delay or saving (Lemma 2 below).

LEMMA 1: *From decreasing marginal utility:*

(*i*) *B is decreasing in Y_1 and constant in Y_2.*

(*ii*) *W is decreasing in Y_1 and Y_2.*

PROOF:

Note that

$$\frac{\partial B}{\partial y_1} = \frac{u'(Y_1) - u'(Y_1 - P)}{2} \tag{4}$$

$$\frac{\partial B}{\partial y_2} = 0 \tag{5}$$

$$\frac{\partial W}{\partial Y_1} = u'(Y_1) - u'\left(\bar{Y} - \frac{P}{2}\right) \tag{6}$$

$$\frac{\partial W}{\partial Y_2} = u'(Y_2) - u'\left(\bar{Y} - \frac{P}{2}\right). \tag{7}$$

Signs follow directly from decreasing marginal utility. ∎

LEMMA 2: *Now we consider the joint distribution of R and $\bar{Y}$. Fix a. If there exist incomes and valuations such that some households save to buy and some households buy immediately, then there is at most a single intersection of B and W such that for low average incomes (below the intersection) the marginal acquiring household buys in period* 1 *(and has correspondingly high valuations), while for higher incomes the marginal acquiring household saves and buys in period* 2.

PROOF:

Since both B and W lines are monotonically nonincreasing in Y_1 and Y_2 it is sufficient to show that W is steeper. Note that $Y_1 = (2 - a)\bar{Y}$ and $Y_2 = a\bar{Y}$, and $a \in [1,2]$, since income is weakly increasing between periods. From Lemma 1, we have that $\frac{\partial W}{\partial Y_2} < \frac{\partial B}{\partial Y_2} = 0$. So, provided that $\frac{\partial W}{\partial Y_1} - \frac{\partial B}{\partial Y_1}$ is bounded above, there is a high enough a for this condition to hold. $\frac{\partial W}{\partial Y_1} - \frac{\partial B}{\partial Y_1}$ is bounded above under a variety of standard assumptions on the third derivative. Online Appendix A outlines these. ∎

Figure 4 depicts the relationship outlined in Lemma 2 in $\bar{Y}$, R space. We hold the ratio of Y_2 to Y_1 fixed, which means plotting the indifference surfaces as lines for a given value of a. The dotted line B is the set of households who are indifferent between buying immediately and never buying. The solid line W, is the set of households who are indifferent between saving in period 1, buying in period 2, and never buying. Households above either line acquire assets.[15]

COROLLARY TO LEMMA 2*: There is an S-shaped curve in ownership at the end of period* 2.

Simply flip the y-axis in Figure 4 and note that those with valuations below the lines do not acquire. The intersection defines a kink. For incomes below the kink,

[15] Note that households above both lines either save or buy. For each income level, there is a cutoff in R such that households above it buy immediately, while households below it, if any, save.

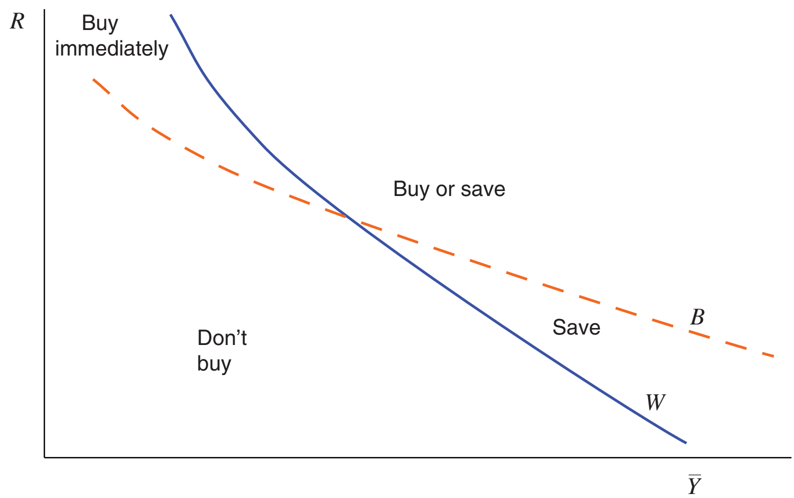

FIGURE 4. EXAMPLES OF NONLINEAR RELATIONSHIP BETWEEN INCOME AND ENERGY USE

Notes: Figure 4 represents the relationship outlined in Lemma 2. Households above indifference curve B strictly prefer to buy in period 1 than to not acquire. Households above indifference curve W strictly prefer to buy in period 2 than to not acquire.

acquisition thresholds rise slowly (the line B is relatively flat). At the kink, the rate of acquisition increases as households move to the steeper W line.

Lemma 3 below follows from another bit of intuition. If second period income is higher than first period income, income growth has effectively forced the household to delay some consumption. Call this "forced savings." For a household who is not saving or purchasing in the second period this reduces welfare because the marginal value of consuming that income in the second period is lower than in the first. However, if the household saves to purchase, the household is not subject to this unequal consumption of the non-asset goods, so the welfare difference increases between saving and purchasing and not purchasing or purchasing immediately. This increase can induce "complimentary savings" where once the household is forced to partially save, the household now might choose to have additional savings.

LEMMA 3: *Hold cumulative income fixed* $(\bar{Y})$, *then increasing period* 2 *income* (Y_2) *reduces period* 1 *purchasers and increases savers/period* 2 *purchasers.*

PROOF:

$$\frac{\partial B}{\partial a} = -\bar{Y}\frac{\partial B}{\partial Y_1}, \tag{8}$$

which is positive from decreasing marginal utility, so there are fewer who buy immediately.

$$\frac{\partial W}{\partial a} = \bar{Y}\Big(u'\big(a\bar{Y}\big) - u'\big((2-a)\bar{Y}\big)\Big), \tag{9}$$

which is negative if income is growing $a > 1$, so there are more savers. ■

Lemma 3 is effectively a point-wise comparison in Figure 4; shifting income from the first period to the second shifts the line B up and the line W down. Lemma 4, below, shows that the magnitude of the shifts in B and W are greater at higher incomes.

COROLLARY TO LEMMA 3: *Income growing fast enough is a sufficient condition for the increase in savers to outweigh the decrease in buyers, and thus, for there to be more total purchasers.*

PROOF:

For there to be more total purchasers, the corollary requires that the increase in savers outweigh the loss of immediate buyers. Note that if $a \to 2$ there are no immediate buyers since first period income does not support immediate purchase. As such, if income is growing fast enough, the corollary holds. ∎

LEMMA 4: *The effects of Lemma* 3 *are increasing in income: at higher cumulative income* $(\bar{Y})$, *the decline in the range of* R *that corresponds to period* 1 *purchasers is greater and the range of* R *that corresponds to savers/period* 2 *purchasers increases at higher cumulative income levels, as long as income growth is fast enough.*

PROOF:

See online Appendix A.

While the model presented in the text is stylized to focus on the clear intuition, we present additional results and discuss a number of important extensions in online Appendix A. We show that our results are robust to complementarities between durables and utility from nondurables and to uncertainty about future income. Indeed, both mechanisms magnify certain results of the model. We also demonstrate that our results, including the nonlinearities we predict, are robust to price changes, multiple assets, and to adding more periods.

C. *Model Predictions*

There are a number of empirically testable predictions from this model.

Prediction 0.—*Acquisition is increasing in income*. With credit constraints, this follows from Lemma 1. Without credit constraints, this follows from the declining marginal utility of income.

Prediction 1.—*There is an S-shaped curve in acquisition*. Without credit constraints, this follows for reasonable distributions of R. This unconstrained setup is consistent with Farrell (1954) and Bonus (1973), who assumed distributions of valuation parameters and income thresholds, respectively, and showed that these lead to S-shaped logit or probit curves for appliance ownership. With credit constraints, this is the corollary to Lemma 2. Note that the mechanisms are orthogonal. The credit constraints mechanism does not depend on distributions of valuations or exogenous income thresholds. This translates into an S-curve in current income, as plotted in Figure 1, for example, as long as there is some positive correlation in period-to-period income.

Prediction 2.—*If there are relatively few period* 1 *buyers, faster income growth leads to delays in acquisition and more ownership at the end of period* 2. Recall that if there are no credit constraints, then for a fixed $\bar{Y}$ faster income growth has no impact on the number of purchasers. There are relatively few period 1 buyers, for example, if incomes are low or refrigerators have low value or are expensive relative to incomes. This prediction, like Lemma 3, is effectively a point-wise comparison in Figure 4 above. It shifts B up and shifts W down. Note that showing an S-shape is not a precise test of the existence of credit constraints because we can get it with either distributions of preferences or credit constraints. This provides another way to validate the importance of credit constraints empirically.

Prediction 3.—*Ownership after period* 1 *is increasing in the interaction of income level and growth*. Follows from Lemma 4.

III. Empirical Context

To better understand the growth in energy demand among low-income households, we analyze asset acquisition in the context of Oportunidades, a conditional cash transfer program in Mexico that was designed to break the intergenerational transmission of poverty. The Oportunidades program is well studied. See Gertler, Martinez, and Rubio-Codina (2012) and Parker and Todd (forthcoming) for additional description. Here we focus on the specifics most relevant to our empirical analysis.

A. *Program Benefits*

Cash transfers from Oportunidades are given to the female head of the household every two months conditional on two criteria. First, all beneficiary households receive a fixed stipend as long as family members obtain preventive medical care and attend pláticas, or educational talks on health-related topics. Second, households also receive educational scholarships conditional on children attending school a minimum of 85 percent of the time and not repeating a grade more than twice. The educational stipend is provided for each child younger than 18 years old enrolled in school between the third grade of primary school and the third grade of high school (twelfth grade) and varies by grade and gender. It rises substantially after graduation from primary school and is higher for girls than boys during high school. Only children who were living in the household when the program started are eligible for the school transfers in order to prevent migration into the household. Total transfers for any given household are capped at a predetermined upper limit.[16]

Table 2 describes the benefits to which beneficiary households were entitled in 2003. While the benefit levels and the grades covered have changed over the course of the program, its basic structure has not. In 2003, the basic support was 155 pesos every two months. The educational scholarship in 2003 ranged between 105 pesos

[16] Compliance was verified through the clinics and schools, who certified whether households actually completed the required health care visits and whether kids attended schools. While full compliance varied, only about 1 percent of households were denied the cash transfer completely for noncompliance.

TABLE 2—OPORTUNIDADES BIMONTHLY SUPPORT LEVELS IN 2003 (*Pesos*)

Basic Support	155	
Educational scholarship		
Grade	Boys	Girls
Third	105	105
Fourth	120	120
Fifth	155	155
Sixth	205	205
Seventh	300	315
Eighth	315	350
Ninth	335	385
Tenth	505	580
Eleventh	545	620
Twelfth	575	655

Notes: A household can receive a maximum of 1,025 pesos with children through sixth grade or 1,715 pesos with children in seventh grade or higher. An additional 200 pesos for children in third to sixth grades and 250 pesos for children in seventh grade or higher are provided once per year for school supplies.

for children in the third grade to 655 pesos for teenage girls in twelfth grade. Finally, Oportunidades provides a yearly stipend to cover the costs of school supplies for children who do not get them at school.

As Table 2 documents, differently composed households are eligible to receive different transfer amounts. For example, households with more female children enrolled in higher grades are eligible for larger educational stipends than similar households with children enrolled in lower levels or with more male children. We can compute the maximum potential transfer for a family by applying the values from Table 2 to the following formula:

$$PT_{it} = \min\left(T_t^{max}, BT_t + \textstyle\sum_s ST_{st} NK_{sit}\right), \tag{10}$$

where PT_{it} is the maximum potential transfer that could be received by household i in period t, T_t^{max} is the program cap on benefits, BT_t is the basic transfer amount that all households receive (the food support), ST_{st} is the educational transfer conditional on a child of type s (i.e., based on grade and gender) attending school, and NK_{sit} is the number of children of type s in household i at baseline aged forwarded to period t. Because of both the benefit schedule and the cap on total benefits, potential transfers are a nonlinear function of the number of children at baseline who could attend the grades eligible for the educational scholarships in period t.

The actual transfers received by a household are less than the potential amount if some children do not attend school. Thus, the actual bimonthly transfer amount received by household i at each time t is computed by using a version of equation (10) that replaces NK_{sit} with a variable measuring the number of children of type s in household i *actually* attending school in period t.

B. *Oportunidades Evaluation and Data Collection*

The data used in this study were generated for program evaluation. At the outset of the program, the government identified marginalized communities in seven states in central Mexico and randomly allocated 320 to be early intervention and

186 late intervention. The original classification scheme designated approximately 52 percent of households as eligible ("poor") (Hoddinott and Skoufias 2004). In the marginalized communities, credit is scarce. Only 1.2 percent of the villages have formal credit institutions, and only 2.8 percent of eligible households have loans of any kind, mostly from friends, neighbors, and relatives (Gertler, Martinez, and Rubio-Codina 2012).[17]

Eligible households in the early intervention communities received benefits starting in April 1998, while households in the late intervention communities did not receive benefits until October 1999. Eligible households were offered Oportunidades and a majority (90 percent) enrolled in the program (Gertler, Martinez, and Rubio-Codina 2012). Once enrolled, households received benefits for at least a nine-year period conditional on meeting the program requirements. No sites were told in advance that they would be participating in the program, information about timing of program rollout was not made publicly available, and there is no evidence of anticipatory behavior (Attanasio, Meghir, and Santiago 2012).

Our analysis focuses on these 506 communities and the panel of approximately 10,000 households that were surveyed from 1997 through 2007. Treatment and control households, which we will refer to as "early" and "late," were similar on a wide array of measured characteristics. Online Appendix Tables 1 and 2 summarize a number of different household-level attributes separately for early and late households. For nearly all of the variables, the means are statistically indistinguishable across the two groups, suggesting that the randomization successfully created comparable groups.

The data used in this study come from the baseline survey, the Encuesta de Características Socioeconómicas de los Hogares (ENCASEH), and the Oportunidades Evaluation Survey (ENCEL), which is a panel dataset. We use all survey rounds in which data were collected about household assets: the first survey, which was administered a year after the program started, during the fall of 1998 and additional surveys from fall 1999, spring and fall 2000, fall 2003, and fall 2007.

The evaluation surveys gather information on a number of potential metrics that the program may affect, including household and household members' characteristics, income and labor supply, expenditure, health and nutritional status, and education, among others. Of particular importance for this study, the survey gathers information on energy-using household durable asset possession, such as refrigerators, gas stoves, televisions, and washing machines.

IV. Empirical Specification and Identifying Assumptions

In this section, we specify the empirical models that we use to test predictions from our model of the relationship between income and durable asset accumulation. Since durable asset purchases are infrequent, discrete events, we model the decision as the probability of purchase in a particular period given that the household has not yet purchased the asset. As such, we estimate linear discrete-time hazard models that take advantage of the panel structure of our data.

[17] Because future income streams from Oportunidades were quite certain relative to income from general economic development, we suspect that credit constraints might bind even more in other environments.

We first test Prediction 0, that the probability of asset purchase is an increasing function of cumulative income, in the context of the following specification:

$$(11)\qquad h(a_{it}) = \Pr(a_{it} = 1 \mid a_{it-1} = 0)$$
$$= \gamma_0 + \alpha_1 \textit{Cumulative Income}_{it} + \beta \mathbf{X}_i + \beta_t \mathbf{F}_i + \mathbf{R}_{rt} + v_{it}\,,$$

where $h(a_{it})$ is the probability that household i acquires appliance a in period t, conditional on not having it in period $t-1$; $\mathbf{X}_i$ is a vector of control variables including household characteristics measured at baseline, which we sometimes replace with a household fixed effect (λ_i); $\mathbf{F}_i$ is a vector of family structure variables, which we interact with round to allow the relationship to vary over time, for example as children age; and $\mathbf{R}_{rt}$ is a vector of state-by-period dummies that help account for any state-specific changes in asset[18] and electricity[19] prices.[20] v_{it} is the random error term. Under Prediction 0, α_1 is positive.

We next test Prediction 1 that there is an S-shaped curve in acquisition. In our context, where all the households are poor, an S-shape implies that higher income households are more likely to use the same increases in income to purchase an appliance. We test this by estimating:[21]

$$(12)\quad h(a_{it}) = \Pr(a_{it} = 1 \mid a_{it-1} = 0)$$
$$= \gamma_0 + \alpha_1 \textit{Cumulative Income}_{it} + \alpha_2 \textit{Cumulative Income}_{it}^2 + \beta \mathbf{X}_i + \mathbf{R}_{rt} + v_{it},$$

where Prediction 1 suggests that α_2 is positive.

Finally, we test Predictions 2 and 3 that, conditional on having the same level of cumulative income, a household which accumulated the income more slowly is less likely to acquire an asset and that this effect is increasing in cumulative income. We use the variation generated from the random assignment of households to begin receiving transfers earlier versus later to test these predictions. We include in the model the variable $\textit{Early}_i$, a dummy indicating that the household began receiving Oportunidades transfers 18 months before the control households, and an interaction of $\textit{Early}_i$ with $\textit{Cumulative Income}_{it}$:[22]

[18] In general, refrigerators are produced on a global market and often imported into Mexico, so prices may largely reflect global trends. Moreover, Oportunidades households are a small share of durable purchases and buy from large retailers in distant urban centers, so prices likely did not respond to transfers.

[19] Mexican electricity tariffs are set at the state level.

[20] Note that previous related papers have examined the impact of income on appliance acquisitions (Dubin and McFadden 1984) and ownership (Dargay, Dermot, and Sommer 2007) using cross-sectional variation in income with limited controls for household demographics. In those specifications, unobserved differences across households may be correlated with income and taste for appliances. One substantial advantage of our empirical setting is that we can take advantage of the large shocks to income that households received via the transfers, and we use both within-household differences brought on by the nonlinear transfer schedule and cross-household difference driven, among other things, by randomization.

[21] We use the same notation for the constant and the coefficients on the control variables in equations (11) to (13), but do not in fact constrain these to be the same across equations.

[22] It is important to note that we are not evaluating the impact of Oportunidades by comparing households in treated and control villages. Instead, we are interested in how the level and timing of transfers affect asset acquisition. The randomization provides exogenous variation in the timing of transfers, but because we also model the effect of cumulative transfers directly, we are not simply comparing treated with control households. To avoid confusion, we have relabeled treated households "early" and control households "late."

$$(13) \quad h(a_{it}) = \Pr(a_{it} = 1 \mid a_{it-1} = 0) = \gamma_0 + \alpha_1 \mathit{Cumulative\ Income}_{it} + \alpha_3 \mathit{Early}_i + \alpha_4 \mathit{Early}_i \times \mathit{Cumulative\ Income}_{it} + \beta \mathbf{X}_i + \mathbf{R}_{rt} + v_{it}.$$

This specification allows us to test Predictions 2 and 3, which suggest that both α_3 and α_4 will be negative.

A. *Measurement of Cumulative Income*

We measure *Cumulative Income*$_{it}$ as the sum of earned wage income for household *i* in time *t*, own enterprise (farm and nonfarm) income, Oportunidades transfers, and non-Oportunidades public and private transfers. The key issue in analyzing this income variable is measurement error that might lead to attenuated and imprecise estimates. Since surveys typically gather information about current income flow, rather than cumulative income, we have to interpolate income between survey rounds adding to the noise in our estimates.[23] In addition, as is common in the developing world, households have substantial informal and enterprise earnings that can suffer from reporting biases.

In addition to measurement error there is a double counting issue if household invest some of the Oportunidades transfers in enterprises that produce income in future periods and we do not observe the costs of those investments. The presence of investment effects may bias the estimated income effects downward.[24] Gertler, Martinez, and Rubio-Codina (2012) do indeed find that households invest a portion of the transfers in agricultural production, providing increases in future income. In online Appendix C, we present results that suggest this creates little, if any, bias.

B. *Cumulative Oportunidades Transfers*

An alternative is to use the variation in cumulative Oportunidades transfers to generate cross-household variation in income. Administrative Oportunidades data provide clean, comprehensive information on the amount and timing of individual transfers. Transfers result in a dollar-for-dollar increase in income if there is no effect of transfers on nontransfer income, an assumption that we discuss and test at length below.

In all but equation (12) we can replace *Cumulative Income*$_{it}$ with *Cumulative Transfers*$_{it}$. However, in (12), it is difficult to detect a convexity in response to cumulative income through a squared term of only one component of income. Instead, we estimate a specification that interacts *Cumulative Transfers*$_{it}$

[23] In many empirical settings, including some of the authors' own work, consumption is used as a measure of household income because it is reported with more precision. However, as we are estimating a model of savings, using consumption as a proxy for income is not appropriate. Indeed the complementary savings effect would cause a relationship between lower consumption and increased asset acquisition.

[24] For example, if a household invests 100 pesos of transfers in 1999 into an endeavor that yields 120 pesos in 2000 (such as farm assets) we will observe the household earning both the 100 pesos in 1999 and the 120 pesos in 2000. Because our model and estimation are in terms of cumulative income, we would measure this household's cumulative income as 220 pesos higher than a household which did not receive the transfer. This will lead us to underestimate the coefficients on income because this household has the same underlying propensity to buy a refrigerator but 100 pesos less in cumulative income than we measure.

with dummy variables indicating whether a household started with low or high assets:

$$(14)\quad h(a_{it}) = \Pr(a_{it} = 1 \mid a_{it-1} = 0)$$
$$= \gamma_1 + \alpha_5 \mathit{Low\ Assets}_i \times \mathit{Cumulative\ Transfers}_{it}$$
$$+ \alpha_6 \mathit{High\ Assets}_i \times \mathit{Cumulative\ Transfers}_{it} + \beta \mathbf{X}_i + \mathbf{R}_{rt} + v_{it},$$

where $\mathit{Low\ Assets}_i$ is an indicator that the household in is in the lower three-quarters of the asset distribution at baseline and $\mathit{High\ Assets}_i$ is an indicator that the household in is in the top quarter of the asset distribution. Under Prediction 1, $\alpha_5 < \alpha_6$.

Replacing $\mathit{Cumulative\ Income}_{it}$ with $\mathit{Cumulative\ Transfers}_{it}$ will lead to unbiased estimates of the income effects if the net impact of transfers on total income is one, i.e., nontransfer income is uncorrelated with transfers. Existing work has examined a number of components of household income that may be correlated with transfers. The literature has found labor supply effects of transfers on youth age 12–14 with relatively low wages,[25] consistent with some of the transfers being conditional on these age children attending school. However, there is no evidence that adult labor supply responds to transfers (Parker and Skoufias 2000 and Skoufias and Parker 2001). Although Albarran and Attanasio (2004) find that transfers lead to statistically significant but small reductions in private remittances to households that receive remittances, only 7 percent of households receive remittances at all. Finally, Gertler, Martinez, and Rubio-Codina (2012) report that households invest a portion of the transfers in agricultural production, but that the size of the investment effect on income is also small (see online Appendix C).[26] Overall, they show that the marginal propensity to consume transfers is 74 percent, which is consistent with the marginal propensity to consume income in other developing countries (Gertler, Martinez, and Rubio-Codina 2012) and thus consistent with a net impact of transfers on total income of one.

Also, since the cumulative transfers that a family receives are determined by choices about whether to keep children in school, it is conceivable that the decision to purchase an appliance would be correlated with household-level shocks that altered the parameters of these choices. For instance, if the household experienced a large positive shock to its nontransfer income, it might be more likely to leave children in school instead of working and simultaneously make the household more likely to acquire an appliance. This would lead to a positive bias in the coefficient on *Cumulative Transfers*.

[25] Parker and Skoufias (2000) and Skoufias and Parker (2001) document that the program reduces child labor and increases enrollment in junior high (secondary) schools as the opportunity cost of these children being in the labor force is now higher. Schultz (2004) also finds positive effects for primary school and junior high school enrollment for boys and girls.

[26] If households invest transfers, then our estimate of the income effect from cumulative transfers specifications are too high. Continuing the example from footnote 24, we attribute the household's response to 100 pesos in transfers, rather than the 120 pesos in income the household actually received. The transfer specifications therefore provide a lower bound and the income specifications provide an upper bound, though in practice both bounds are qualitatively similar and are consistent with our predictions.

C. *Instrumenting with Potential Transfers*

We estimate separate models using *Cumulative Income* and *Cumulative Transfers* and therefore need to address both the measurement error in *Cumulative Income* and potential omitted variable bias in *Cumulative Transfers*. We solve both of these problems through instrumental variables using *Potential Cumulative Oportunidades Transfers* (PCT), the transfers a household had the potential to earn if they enrolled and fully complied, as the instrument. It is computed assuming that all eligible children enrolled at baseline are still in school and have advanced one school grade per school year, and therefore by construction is uncorrelated with adult and child labor supply, enterprise income, and other nonlabor income.

There is exogenous variation in PCT both within a given household over time and across households. The cross-sectional variation at a point in time depends on when the family entered the program and the rate of accumulation since entry. While the time the household was incorporated into the program was randomized, the rates at which potential cumulative transfers change over time are a nonlinear function of school grade and gender of school-age children.

The nonlinearities arise from the program rules described above. Rates of accumulation within a household vary with time as younger children age into the program, as they progress through school, and as children age out of the program. There are very large nonlinearities as children enter fourth grade, secondary school, high school, graduate high school, and based on gender. In addition, in 2000, Oportunidades extended the payments for grades 10–12. These rules generate substantial exogenous nonlinear variation in the transfer amounts across households as well as within households over time. PCT is a sufficient statistic for all of these nonlinearities. Differences in household demographics and initial program participation dates drive differences in PCT between households. As households cross the various nonlinear payment thresholds, PCT picks up differences within households over time. Moreover, the cap on total per-period benefits creates another nonlinearity that interacts with all of the other nonlinearities.[27]

To better understand the extent to which different factors drives variation in PCT we decomposed the variance as follows:

$$\text{var}(PCT_{it}) = \text{var}(\delta_i) + \text{var}(\mathbf{R}_{rt}) + 2\text{cov}(\delta_i,\mathbf{R}_{rt}) + \text{var}(\varepsilon_{it}), \tag{15}$$

where δ_i and R_{rt} represent the household and region-by-period fixed effects, respectively, and ε_{it} is a random error term. Our calculations suggest that region-by-period fixed effects account for about 55 percent of the variation, household fixed effects account for about 30 percent of the variation, and the covariance between the two terms is effectively zero. This suggests that there is substantial remaining variation

[27] An alternative identification strategy would try to exploit one or two specific nonlinearities using ad hoc specifications. We reject this for several reasons. First, the cumulative transfer formula is the parameterization of the instrument that incorporates all of the nonlinearities and their interactions. Since this parameterization is the one actually faced by families and summarizes all the nonlinearities, then it should have more predictive power than other limited ad hoc parameterizations. Second, by focusing on one or two nonlinearities we would be ignoring other relevant variation and we would lose potentially substantial predictive power.

within household to help identify the effects of transfers in the specifications with household and region-by-period fixed effects.

Because some of our specifications rely on cross-household variation, we also estimated the share of the variance accounted for by household factors that might reasonably impact appliance valuations. When we include indicator variables for household size and the age structure of household members instead of household fixed effects, these variables explain less than 15 percent of the variation in transfers. These decompositions suggest that the randomization, differences in transfers driven by household gender and age-composition of children, and the nonlinearities in these transfer schedules account for a substantial share of our variation.

One potential concern is that potential cumulative transfers may be correlated with household demographic structure and the demographics may affect the demand for energy-using assets. We address this by explicitly controlling for household demographic structure in the models. Also, note that potential cumulative transfers are not strongly correlated with the number of children in the household. To see this, compare a household with three girls in grade two of primary school and a household with three girls in grade eight (junior high school). Both households have three female children but while the first household will receive no school transfers in the current period, the latter household will receive a large monthly transfer. In addition, families with four or more children in junior high school would receive the same transfer amount as the latter household because the cap on total benefits would be binding. Thus, we are able to explicitly control for household size and the number of children in the household in the empirical specification and still have substantial variation in cumulative transfers to identify the coefficient on that variable.

There may be lingering concerns that household demographic structure is correlated with both the potential cumulative transfer amounts and the propensity to purchase appliances. For instance, households with older girls may have systematically different refrigerator valuations than households with younger girls. We explicitly test to see whether baseline appliance ownership is correlated with future cumulative transfers and therefore with household demographic structure embedded in the transfer formula. Specifically, we will present results from placebo tests that suggest that the nonlinear function that translates family structure to potential cumulative transfers does not predict appliance ownership at baseline (i.e., before the program started). So, as long as any changes in the propensity to buy a refrigerator after the baseline survey were similar across households with different family structures, our specification will yield unbiased estimates of our coefficients of interest.

D. *Interaction Terms*

In equation (13) some specifications include the interaction $Early_i \times Cumulative\ Transfers_{it}$ in order to measure differences in refrigerator acquisitions between early and late households who have had the same level of cumulative transfers. While variation in $Early_i$ in equation (13) is generated by the random assignment of households to begin receiving transfers early versus late, we also want to be sure that the distributions of cumulative transfer levels overlap between the early and late groups. Otherwise, we could simply be picking up nonlinearities in the relationship between cumulative transfers and appliance acquisition.

TABLE 3—SUMMARY STATISTICS: CUMULATIVE TRANSFERS (*Ten Thousands of 2003 Pesos*)

	Late households			Early households		
	25 percent	Median	75 percent	25 percent	Median	75 percent
1998				0.09	0.13	0.21
1999				0.24	0.38	0.61
2000m	0.06	0.09	0.16	0.32	0.51	0.82
2000n	0.18	0.33	0.53	0.45	0.79	1.23
2003	0.93	1.69	2.63	1.24	2.19	3.36
2007	2.36	3.89	5.67	2.63	4.33	6.35

Notes: Data from the survey administered in spring 2000 is denoted by 2000m. Data from the survey administered in fall 2000 is denoted by 2000n.

Source: ENCEL surveys and administrative data

Table 3 reports cumulative transfer amounts over time for households in the early and late groups that are at different parts of the transfer distribution. We see that households at the seventy-fifth percentile of the late group had higher cumulative transfer amounts than both households at the twenty-fifth percentile of the early group by late 2000 and the median of the early group by 2003. This suggests that we have considerable overlap between the distributions of cumulative transfers by 2003.[28]

In equation (14) we interact $Cumulative\ Transfers_{it}$ with the indicator $Low\ Assets_i$ in order to test heterogeneous treatment response of wealthier households as predicted by the model. Variation in baseline $Low\ Assets_i$ reflects households' pretreatment wealth and income, and may have various endogeneity concerns. For example, households with more animals may simply value assets more. However, in all our relevant specifications, we control for a household's baseline asset ownership.[29]

V. Empirical Results

Our analysis focuses on refrigerator acquisitions, by far the most expensive and most energy-intensive household appliance for the Oportunidades population. The results for refrigerators are robust for other assets as we discuss below. In addition, while we report specifications estimated using both *Cumulative Income* and *Cumulative Transfers*, we favor the results estimated with transfers. The results are very similar for both, but transfers are measured with much more precision.

A. *Descriptive Evidence*

We begin with descriptive support for the theoretical predictions. Figure 5 plots cross-sectional refrigerator ownership as of 2003 on *Cumulative Transfers* through

[28] We focus on observations through 2003. As the initial randomization is the only source of difference between early and late households, additional years mute the variation between the two groups. If we include later years in our estimates of equation (13), the coefficient estimates are attenuated to zero slightly, as we would expect with more noise relative to systematic differences between the groups, but are very similar to the results we present.

[29] In the models reported in the paper we use the value of animal assets to measure $Low\ Assets_i$. Alternate measures of household wealth, such as total household consumption or consumption per capita, yield similar differences between the relatively better off and less well-off households.

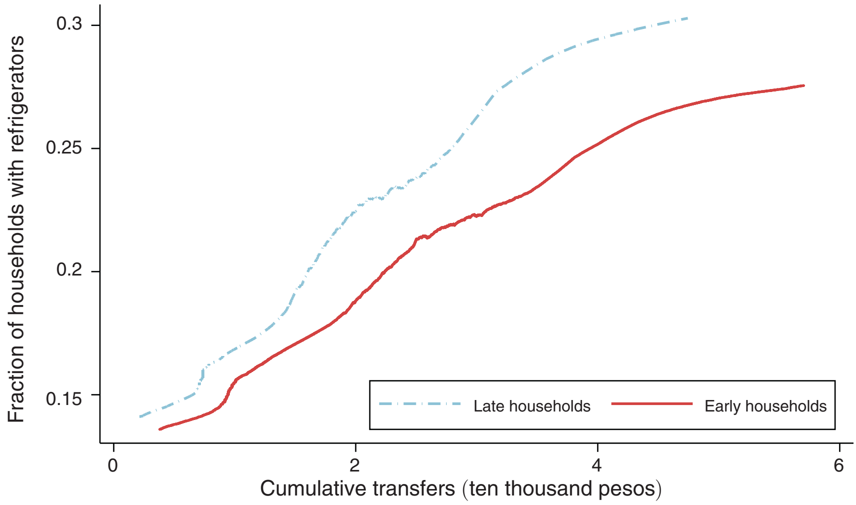

Figure 5. Refrigerator Ownership and Cumulative Transfers in 2003

Notes: LOWESS regressions. Excludes the bottom and top 2 percent of cumulative transfers in each group.

Sources: ENCASEH (1997) and ENCEL (1998, 1999, March 2000, November 2000, 2003, and 2007) surveys and administrative data. See online Appendix. Reflects only households who do not have refrigerators at baseline.

2003 separately for *Early* and *Late* households.[30] Following Prediction 0 we expect upward-sloping ownership curves ($\alpha_1 > 0$). Prediction 1 predicts that these curves are convex, i.e., increasing in other components of wealth ($\alpha_2 > 0$). Prediction 2 suggests that the line for *Early* households is below the line for *Late* households ($\alpha_3 < 0$), while Prediction 3 implies that the line for *Early* households is less steep than the line for *Late* households ($\alpha_4 < 0$). Figure 5 is consistent with these predictions.[31]

B. *Income Effects*

Table 4 presents the results for several specifications of equation (11) that test Prediction 0. We estimate (11) using linear regression and report robust standard errors clustered at the village level. All specifications include state-by-round fixed effects and either a number of household controls or household fixed effects (FE). The first three columns report results based on *Cumulative Transfers*$_i$ while the last three report results based on *Cumulative Income*$_i$.

The coefficient on *Cumulative Transfers* (α_1) in the first three columns is positive and highly statistically significant. Column 1 reports the OLS estimate, column 2 reports the instrumental variable (IV) estimate with household controls using *PCT* to instrument for *Cumulative Transfers*, and column 3 reports the IV estimates replacing the household controls with household fixed effects. The instrument is

[30] The survey only collected information on whether the household has a refrigerator at the time of the survey and not on the type of refrigerator owned.

[31] Though there are convex regions, the convexity of Prediction 1 is not obvious in the figure. In Section VC we test for convexity explicitly including controls.

TABLE 4—BASIC RESULTS: REFRIGERATOR (*Income Effects*)

	Discrete time hazard		Household FE	Discrete time hazard		Household FE
	OLS	IV	IV	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative Transfers	0.018***	0.020***	0.047***			
	[0.005]	[0.007]	[0.008]			
Cumulative Income				0.003***	0.016***	0.034***
				[0.001]	[0.005]	[0.007]
Observations	30,414	30,414	30,258	30,414	30,414	30,258
R^2	0.103			0.104		
Kleibergen-Paap Wald F-Stat on excluded variables		2,503	2,060		92	108
Number of households			6,655			6,655

Notes: All specifications include state by round-fixed effects. Rounds through 2003 included. All specifications include household age structure controls including number of children 7 and younger, number of children 8 to 17 years old, number of males 18 to 54, number of females 18 to 54, number of adults 55 and older, number of individuals with unreported ages, interacted with round fixed effects. Specifications in columns 1, 2, 4, and 5 include head of household's gender, head of household's and spouse's age and education, and whether the household owns the house they live in, farm assets at baseline, number of other social programs the household is the beneficiary of, and village characteristics including migration intensity, marginalization, and distance to nearest city. In column 2, 3, 5, and 6 the excluded instrument is PCT. Columns 3 and 6 include household fixed effects and drop 156 singletons. Robust standard errors clustered by village in brackets.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

extremely strong as indicated by the first-stage F-statistics, which exceed 2,000. The coefficient estimates in (2) are very similar to the OLS estimates in (1). However, the IV FE estimate in (3) is more than twice as big as the OLS and IV estimates in (1) and (2).[32]

The magnitude of the estimated coefficient in column 3 suggests that for every 10,000 pesos increase in a household's cumulative transfers, the probability that it acquires a refrigerator goes up by 4.7 percentage points off of a baseline ownership of 4 percent.[33] Mean cumulative transfers in 2003 explain 55 percent of refrigerator acquisition between baseline and 2003.

Columns 4 through 6 repeat these estimates using *Cumulative Income*. The large magnitude difference between column 4 and 5 is consistent with the IV approach correcting for the much larger measurement error in income. The coefficients estimated by IV using *Cumulative Transfers* in columns 2 and 3 and those estimated using *Cumulative Income* in columns 5 and 6 are similar in magnitudes and significance.[34] One important difference, however, is in the power of the first stage. The

[32] It is possible that the coefficient on *Cumulative Transfers* is larger in column 3 in part because the household fixed effects capture whether the household was in the early or late wave of program treatment, which we show below is an important factor in determining refrigerator purchases.

[33] We opt not to estimate a traditional income elasticity. Indeed, as our conceptual framework suggests, the likelihood of acquiring an asset with an increase in current income depends not only on that income, but on past income accumulated as wealth and the time path of future income. Unlike in stable settings with well-functioning capital markets, current income is not a good proxy for a household's expected path of income.

[34] We discussed above why measurement and data issues make the transfers effect potentially too large, and the income effect too small.

F-statistics are substantially lower in the income specifications in columns 5 and 6 compared to the transfers specifications in columns 2 and 3.

C. *Nonlinearity in Income and Wealth Effects*

We now test the hypothesis that the income effects are increasing in income (Prediction 1), using the specification in equation (12) that includes both *Cumulative Income* and *Cumulative Income*^{2}.[35] As instruments we use *PCT* and *PCT* interacted with the value of assets at baseline.[36] The results, reported in Table 5, indicate a convex relationship between cumulative income and asset acquisition; i.e., $\alpha_2 > 0$ in equation (12). The magnitudes suggest that the income effect of the 75 percent percentile household in 2003 is nearly twice that of the median household.[37]

These results are consistent with an S-shaped relationship between income and asset ownership. Since all households in the sample are poor, at baseline we would expect most of them to be at cumulative income levels below the acquisition cutoff, i.e., the first inflection point on the S-curve. We would also not expect any households to pass the second inflection point. As households enter the program, the slightly better off should be more likely to acquire the asset at a given level of transfers than those that are poorer leading to the first inflection point.

We find similar results when we estimate the specification in equation (14) and allow the effects of transfers on asset acquisition to differ for households in the top 25 percent of asset ownership at baseline versus the bottom 75 percent. This allows us to identify the Oportunidades households that are relatively better off and closer to the acquisition inflection point on the S-curve. Indeed, the results reported in Table 6 show that the effect of transfers on acquisition is larger for households that started off wealthier. The coefficients from column 2 suggest that 10,000 pesos in cumulative transfers leads to a 1.5 percentage point increase in ownership by poor households, while wealthier households increase ownership by 3.1 percentage points. These results are consistent with the importance of credit constraints steepening the S-curve. Income specifications of this interaction, reported in online Appendix C, show similar, though less precise results.

[35] For this specification we add to each household's cumulative income the value of their animal assets at baseline. We use baseline assets to measure initial savings from cumulative income prior to the period of analysis. In rural Mexico, few households in this population have access to banks. Rural households in low-income countries typically do not hold savings in cash, but rather hold savings in more easily liquefiable assets such as animals (Rosenzweig and Wolpin 1993). As such, we measure the value of assets in our study as the value of animals. Household asset ownership at baseline, then, is a measure of the households' unconsumed previous income. Thus, conditioning on baseline assets, any income that household earned prior to baseline that was not saved, could not influence future consumption and asset purchase decisions. If the primary savings vehicles are these assets, then we have correctly captured the household's wealth at baseline. Baseline animal assets are controls in all specifications, so this change is only relevant for the nonlinearity.

[36] Another potential instrument is *PCT*^{2}. In specifications that include this, the power of the first stage is lower and estimates are not statistically different from those reported in Table 5. This is because there is little nonlinearity in the relationship between *Cumulative Income* and *PCT* conditional on the rich set of controls. See online Appendix Figure 1.

[37] Marginal effect at median income (12.4 ten thousand pesos) $= 0.0059 + 12.4 \times 0.0009 = 0.0053$. At seventy-five percentile (16.9 ten thousand pesos) $= 0.0059 + 16.9 \times 0.0009 = 0.0093$.

TABLE 5—BASIC RESULTS: REFRIGERATOR (*Nonlinear Income Effects*)

	Discrete time hazard		Household FE
	OLS	IV	IV
	(1)	(2)	(3)
Cumulative Income	−0.0007	−0.0059	0.0132
	[0.0011]	[0.0108]	[0.0132]
Cumulative Income ^{2}	0.0001***	0.0009**	0.0008**
	[< 0.0001]	[0.0004]	[0.0004]
Observations	30,414	30,414	30,258
R^2	0.105		
Kleibergen-Paap Wald *F*-Stat on excluded variables		22	23
Number of households			6,655

Notes: All specifications include state by round-fixed effects and household controls and column 3 includes household-fixed effects as described in the notes to Table 4. In column 2 and 3 excluded instruments are *PCT* and *PCT* × *Baseline Animal Assets*. Robust standard errors clustered by village in brackets.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

TABLE 6—BASIC RESULTS: REFRIGERATOR (*Wealth Effects*)

	Discrete time hazard		Household FE
	OLS	IV	IV
	(1)	(2)	(3)
Low Assets × *Cumulative Transfers*	0.014***	0.014***	0.041***
	[0.005]	[0.007]	[0.009]
High Assets × *Cumulative Transfers*	0.029***	0.032***	0.058***
	[0.006]	[0.008]	[0.009]
Difference	0.015***	0.018***	0.017***
	[0.005]	[0.006]	[0.006]
Observations	30,414	30,414	30,258
R^2	0.104		
Kleibergen-Paap Wald *F*-Stat on excluded variables		1,252	1,025
Number of households			6,655

Notes: All specifications include state by round-fixed effects and household controls and column 3 includes household-fixed effects as described in the notes to Table 4. Columns 1 and 2 also include *High Assets* as a household control. In columns 2 and 3, excluded instruments are *Low Assets* × *PCT* and *High Assets* × *PCT*. Robust standard errors clustered by village in brackets.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

D. *Timing Effects*

Table 7 presents several specifications of equation (13), which we use to test Predictions 2 and 3 related to timing. The first column, repeated from column 1 of Table 4, reports the basic cumulative transfer effect. When we include the *Early* dummy in column 2, the coefficient on *Early* is negative as predicted and highly significant. The magnitude suggests that being in the late group is equivalent to about a 6,000 pesos increase in cumulative transfers for the early group.

Table 7—Basic Results: Refrigerator (*Timing Effect*)

	Discrete time hazard				Household FE
	OLS	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)
Cumulative Transfers	0.018***	0.023***	0.035***	0.053***	0.063***
	[0.005]	[0.005]	[0.007]	[0.010]	[0.010]
Early		−0.014***	−0.006	−0.008	
		[0.005]	[0.005]	[0.005]	
Early × *Cumulative Transfers*			−0.014**	−0.021***	−0.018**
			[0.006]	[0.007]	[0.007]
Compensating transfer at 2003 median *Cumulative Transfers* (ten thousand pesos)			1.857**	1.727***	
			[0.859]	[0.599]	
Observations	30,414	30,414	30,414	30,414	30,258
R^2	0.103	0.104	0.105		
Kleibergen-Paap Wald *F*-Stat on excluded variables				1,058	1,072
Number of households					6,655

Notes: All specifications include state by round-fixed effects and household controls and column 5 includes household-fixed effects as described in the notes to Table 4. Column 1 is the basic cumulative transfer effect repeated from Table 4. Robust standard errors clustered by village in brackets.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

When we include the interaction between *Early* and *Cumulative Transfers* in column 3, the interaction term is negative and statistically different from zero, while the coefficient on the *Early* dummy drops in absolute value. As the coefficient on the *Early* dummy in column 3 reflects the early effect at zero cumulative transfers, which is outside the range of our data, we also report the "Compensating Transfer at 2003 Median Cumulative Transfers,"[38] which is the amount of additional transfers the median early household would need to have the same acquisition rate as a late household with median cumulative transfers. Graphically, this number maps to Figure 5. Take the median household on the *Early* households line (solid line) and compare it to the *Late* households line (dashed line) at the same Cumulative Transfers. The compensating transfer reflects the distance we would need to move the early household to the right along the solid line until it had the same acquisition rate as the late household.

Column 4 of Table 7 instruments for both *Cumulative Transfers* and *Early* × *Cumulative Transfers* with *PCT* and *Early* × *PCT*. The instruments are extremely strong, and the first-stage *F*-statistic, reported at the bottom of column 4, exceeds 1,000. The IV coefficient estimates are very similar to the OLS estimates in column 3. If anything, the IV coefficient on *Cumulative Transfers* is slightly higher. The coefficients from column 4 suggest that 10,000 pesos in cumulative transfers lead to 5.3 percentage points of acquisition by late households, but only 2.4 percentage points of acquisition by early households.

In column 5, we include household fixed effects, which allow us to control for any remaining differences across households not picked up by the household

[38] The coefficient estimated is $\gamma_\tau = -\dfrac{\alpha_4 \times MedianTransfersEarly + \alpha_3}{\alpha_1 + \alpha_4}$.

controls included in columns 1 through 4.[39] We have within-household variation in cumulative transfers because of the nonlinear increases in transfers depicted in Table 2 and because children age into or out of the program. We cannot estimate the *Early* dummy as this is a time-invariant household characteristic. The specification in column 5 uses IV estimation, and is therefore comparable to the results in column 4. The coefficient estimates on *Cumulative Transfers* and *Early* × *Cumulative Transfers* are remarkably similar across columns 4 and 5 suggesting that our household controls pick up most cross-household differences in tastes.

Table 7A replicates these specifications using *Cumulative Income* as the endogenous variable. Despite the significantly higher measurement error, the results are qualitatively similar, and the IV specifications appear to at least partially address the measurement error. Perhaps the most straightforward comparison is the compensating transfer that the median early household would need to receive to acquire at the same rate as late households. We estimate the compensating transfer using the coefficients from columns 4 of Tables 7 and 7A to be very close: 17,000 pesos in the transfers specification and 15,000 pesos in the income specification.

Other Assets.—Online Appendix D and online Appendix Table 7 present the main results from Tables 4 to 7 for additional energy-using assets. Our statistical power and the segment of the households included in the specifications both vary by assets. For example, most households have radios at baseline, reducing the estimation sample significantly and focusing the estimation on the poorest households. The results for income, nonlinearities in income, and wealth effects are supportive of our model. For all but two assets, the income, nonlinear income, and wealth effects are all positive as predicted.[40] The magnitudes of these parameters should not be directly compared because these assets provide different levels of utility and thus increases in income should be expected to produce different increases in acquisition depending on the asset. The comparison of the compensating transfer in the timing effect is comparable across assets. For all but one asset, the compensating transfer in online Appendix Table 7 are statistically indistinguishable from the refrigerator effect, and the one which is distinguishable is Gas Stoves where the timing effect is even larger.

E. *Alternative Explanations*

While the results presented so far are consistent with the model presented in Section II, they may also be consistent with a number of alternative explanations. In this section we investigate the most obvious ones.[41]

[39] For example, while the household controls include the number of children, we do not include precise variables measuring their exact gender and age makeup. If across households with the same number of children, the households with older girls, for instance, had higher valuations for refrigerators than the households with younger boys, the coefficient on *Cumulative Transfers* might be biased positive. This could in turn lead to a negative bias on the early dummy as, for a given level of cumulative transfers, the early households are more likely to be comprised of young boys.

[40] Fan ownership was not collected after 2001, so all the households had received transfers and power is significantly reduced. Gas water heaters show little penetration or acquisition, perhaps indicating that even the higher income households are still too poor to acquire them.

[41] For brevity we present transfer specifications. Income specifications are similar.

Table 7A—Basic Results: Refrigerator (*Timing Effect, Cumulative Income*)

	Discrete time hazard				Household FE
	OLS (1)	OLS (2)	OLS (3)	IV (4)	IV (5)
Cumulative Income	0.003***	0.003***	0.004***	0.031***	0.039***
	[0.001]	[0.001]	[0.001]	[0.007]	[0.008]
Early		−0.005	< 0.001	0.005	
		[0.005]	[0.005]	[0.007]	
Early × *Cumulative Income*			−0.001	−0.004**	−0.003
			[0.001]	[0.002]	[0.002]
Compensating income at 2003 median *Cumulative Income* (ten thousand pesos)			3.799	1.499**	
			[3.715]	[0.585]	
Observations	30,414	30,414	30,414	30,414	30,258
R^2	0.104	0.104	0.104		
Kleibergen-Paap Wald *F*-Stat on excluded variables				38	48
Number of households					6,655

Notes: All specifications include state by round-fixed effects and household controls and column 5 includes household-fixed effects as described in the notes to Table 4. In columns 4 and 5, excluded instruments are *PCT* and *Early* × *PCT*. Robust standard errors clustered by village in brackets.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Future Expectations.—The variable *Early* may be an indicator for lower expected future transfers and thus the negative coefficient could simply represent lower expected income. Specifically, among early and late households with the same cumulative transfer levels at a given point in time, early households might expect lower transfers in the future since their average transfer rate is lower than the late households.[42] For instance, late households may simply have more girls than early households who are at the same level of cumulative transfers in 2003.

Table 8 presents results from several specifications that include measures of future transfers as additional explanatory variables. Column 1 of Table 8 reproduces column 3 of Table 7, and then columns 2 and 3 add information about the household's actual future transfers through 2007.[43] With rational expectations, realized future transfers proxy for expected transfers. The alternative hypothesis put forward above would suggest that the coefficient on *Future Cumulative Transfers* should be positive. In fact, we find that it is either undetectably different from zero or statistically significant and negative. A negative coefficient is consistent with the intertemporal optimization underlying our framework in Section II, as it suggests that households expecting higher transfers in the future are less likely to buy an asset now, presumably because they are waiting to buy it when their income is higher.

[42] Because transfer rates vary over time within a household, increasing as younger children enter higher grades and decreasing as older children age out of the program, it is also possible that an early household will have the same cumulative transfers as a late household, but will have *higher* expected transfers. For example, the early household could have begun with younger children, accumulating slowly, while the late household began with older children—accumulating quickly at first, but then slowly later when its children age out of the program.

[43] Specifically, *Future Cumulative Transfers* are the amount of transfers the household will receive through 2007 less the transfers the household has already received. We interact this with the round and instrument with *Future PCT*.

Table 8—Future Transfers and Refrigerator Acquisition

	OLS (1)	OLS (2)	IV (3)
Cumulative Transfers	0.035***	0.031***	0.103***
	[0.007]	[0.008]	[0.011]
Early	−0.006	−0.005	−0.020***
	[0.005]	[0.005]	[0.007]
Early × *Cumulative Transfers*	−0.014**	−0.014**	−0.029***
	[0.006]	[0.006]	[0.008]
Compensating transfer at 2003 median *Cumulative Transfers* (ten thousand pesos)	1.857**	2.058*	1.173***
	[0.859]	[1.099]	[0.250]
Future Cumulative Transfers × 2003		0.006	−0.079***
		[0.005]	[0.024]
Future Cumulative Transfers × 2000*n*		−0.004***	−0.013***
		[0.001]	[0.004]
Future Cumulative Transfers × 2000*m*		0.001	−0.009***
		[0.002]	[0.003]
Future Cumulative Transfers × 1999		$<$0.001	−0.002
		[0.001]	[0.002]
Future Cumulative Transfers × 1998		$<$0.001	$>$−0.001
		[0.001]	[0.002]
Kleibergen-Paap Wald *F*-Stat on excluded variables			29
Observations	30,414	30,414	30,414
R^2	0.105	0.105	

Notes: All specifications include state by round-fixed effects and household controls described in the notes to Table 4. In column 3 excluded instruments are *PCT*, *Early* × *PCT*, and *Potential Future Cumulative Transfers* by round. Column 1 repeats results from Table 7. Robust standard errors clustered by village in brackets.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Recertification.—Recertification could also make households forward looking. While households are promised payments for six more years after not being recertified as eligible, households may delay or avoid purchasing refrigerators to maintain future eligibility. This would bias the results of our main specification toward zero as current cumulative transfers are positively correlated with future transfers, and households with more at stake in the future would presumably be more reluctant to purchase a refrigerator to ensure continued participation in the program. The results in Table 8 are consistent with this. Controlling for future transfers, and thus the benefits of recertification, leads to bigger effects of transfers.

Self-Control.—We also considered the possibility that the difference in acquisition is driven by a lack of self-control. Particularly, the logic of the intertemporal optimization in Section II suggests that early households have the ability to replicate through saving the time path of transfers of the late households, but instead choose to allocate transfers differently. However, if these households lack self-control or access to savings vehicles, or are otherwise myopic it is possible that the temporal effects we observe are the consequence of households spending the transfers as they receive them, rather than optimizing considering both current and future transfers. The negative coefficients on *Future Cumulative Transfers* in Table 8, however, are not consistent with lack of self-control or other myopic behavior.

Family Structure.—Another concern is that the nonlinear relationship between income and refrigerator acquisition reflects differences in both tastes and income across families with different structures. For example, the *Early* dummy is identified by considering households with the same cumulative income, some of whom received transfers steadily at low rates and some of whom received no transfers for 18 months and then high transfers once they began the program. Because of the randomization, the households in the early and late groups are similar on average. However by construction, households in the two groups with the same cumulative transfers have different family structures. The fact that specifications estimated with household fixed effects suggest larger effects than specifications that simply include household-level controls gives us reassurance that taste differences across households are not driving our results.

F. *Placebo Tests*

As an additional robustness check, we estimated cross-sectional placebo specifications using asset ownership before the households began receiving transfers. These specifications test whether the particular nonlinear relationship between family structure and transfers embodied in cumulative transfers predicts appliance ownership prior to the impact of the transfers themselves. The results are presented in Table 9. Each specification is estimated using instrumental variables and including household controls, comparable to the specification reported in column 4 of Table 7. Column 1 uses ownership from the baseline survey that was conducted in 1997 and cumulative transfers through 2003. The coefficients on *Cumulative Transfers*, *Early*, and *Early* $\times$ *Cumulative Transfers* are insignificantly different from zero.[44] This provides additional reassurance that the differential transfer rates experienced by households under Oportunidades are not systematically correlated with the propensity to acquire appliances.

Since the specifications at baseline in Table 9 are cross-sectional while the results in Table 7 were estimated as discrete time hazards, we estimated similar specifications for 2003 by way of comparison. These are presented in column 4. These specifications confirm the results in Table 4 and Table 7.

Columns 2 and 3 report another variant of the placebo test that predicts asset ownership in the period just before a household entered the program (baseline for treated households and 1999 for control households) as a function of the household's first-period transfers. These tests do not capture the variation induced by the randomization, but do use transfers in a period closer to the period in which households' baseline asset ownership is measured. If there were meaningful correlations between family structure (and thus transfer rates), such as the ages of children and girls versus boys and valuations of refrigerators, we should expect a relationship

[44] Results are similar for placebo tests on other assets.

TABLE 9—PLACEBO TEST: DO CUMULATIVE TRANSFERS PREDICT REFRIGERATOR OWNERSHIP AT BASELINE?

	Baseline ownership	Baseline ownership	1999 ownership	2003 ownership
	All households (1)	Early households (2)	Late households (3)	All households (4)
Cumulative Transfers (2003)	0.006			0.054***
	[0.006]			[0.012]
Early	0.005			0.029
	[0.012]			[0.026]
Early × *Cumulative Transfers* (2003)	−0.001			−0.030***
	[0.005]			[0.011]
Cumulative Transfers (1998)		0.066		
		[0.151]		
Cumulative Transfers (2000*m*)			0.120	
			[0.224]	
Compensating transfer at 2003 median cumulative transfers (ten thousand pesos)	−0.675			1.686**
	[1.731]			[0.875]

Notes: Columns 1–3 report results from three different placebo cross-sectional specifications, where the dependent variable is refrigerator ownership before transfers. For comparison, column 4 reports results using refrigerator ownership in 2003 as the dependent variable. All specifications include state-fixed effects and household controls, as described in the notes to Table 4. Columns 1 and 4, estimated using IV with *PCT* and *Early* × *PCT* as instruments, show no relationship between cumulative transfers at through 2003 and baseline ownership. Columns 2 and 3, estimated using IV with PCT as excluded instrument, show no statistical relationship between cumulative transfers in the first period available and ownership at the cross-section immediately prior to the beginning of transfers. Robust standard errors clustered by village in brackets. Kleibergen-Paap Wald *F*-stat on excluded variables not reported. All exceed 75.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

between first-period transfer rates and asset ownership driven by preferences and not transfers. This test takes advantage of the fact that households with high first-period transfers are those with older and more female children, not necessarily those who will eventually have high cumulative transfers. Though noisier, these similarly show no statistically significant impact of first-period transfers. These tests also refute the hypothesis that household preferences for appliances change over time in a manner correlated with the transfer schedule, for example, if households with nine-year-old boys had similar preferences to households with nine-year-old girls, but preferences diverged when the children were in their teens.

VI. Conclusions

We develop a model and provide empirical analysis to demonstrate that households faced with credit constraints become much more likely to purchase energy-using assets with additional income once their income passes a threshold level. The timing of asset purchases in our data is also consistent with predictions from theory. Specifically, though households randomized to receive Oportunidades transfers earlier than other households faced greater expected benefits over the life of the program, they were less likely to acquire refrigerators. Given that refrigerators are long-lived assets, this is inconsistent with perfect capital markets and forward-looking consumers.

Over the next several decades, wide-scale poverty alleviation programs as well as continued economic growth will lift the incomes of many of the world's poor. At the same time, governments, major multilateral and bilateral aid organizations, and private companies are spending hundreds of billions of dollars a year rolling out energy infrastructure in the developing world. As incomes rise and as energy access increases, families formerly living in poverty will for the first-time purchase refrigerators, water pumps, air conditioners, washing machines, vehicles, and other energy-using assets.

Our results have implications for both micro- and macro-level policies. Our results speak to the potential impacts of credit availability on asset acquisition. There is anecdotal evidence that retailers are beginning to sell appliances on credit in some parts of the developing world. For example, Wal-Mart's Banco de Wal-Mart recently began offering credit cards for purchases at Wal-Mart. This appliance-directed credit should lower the income levels at which households acquire appliances, but also could reduce the aggregate nonlinear relationship between income and energy use at a macro level. Our results also show that the time path of the payments in government transfer programs may impact asset acquisition rates. In the presence of credit constraints, the timing and frequency of transfer payments and the path of economic growth are important determinants of asset acquisition, not just transfer amounts.

As more and more households in the developing world become first-time owners of energy-using assets like refrigerators and vehicles, policies that promote more energy-efficient appliances, such as subsidies for high efficiency models, labeling or other information programs, or minimum efficiency standards, become increasingly important. While a considerable literature considers US households' willingness to trade off a high upfront cost for an energy efficient model versus lower usage costs, more work needs to be done to understand household energy efficiency decisions in the developing world, where the range of products offered, information about efficiency, energy prices, credit availability, and industrial organization of appliance sales all may differ.[45]

At a more macro level, our results could help improve the accuracy of energy demand forecasts. While energy forecasters concur that the bulk of the growth in energy demand and associated greenhouse gas emissions is likely to come from the developing world (EIA 2013; International Energy Agency 2014), existing forecasts have not allowed for the possible nonlinear relationship between income growth, especially pro-poor growth, and energy demand suggested by our model (Wolfram, Shelef, and Gertler 2012). For example, we find evidence of this when we look historically at near-term forecasts and compare them to realized energy demand. For example, in its World Energy Outlook 2000, the Energy Information Administration forecast that China's energy demand in 2005 would be 55 quadrillion BTUs. Actual energy demand that year was a stunning 25 percent higher. In part, this reflects the fact that the EIA underestimated China's GDP growth, but even adjusting for

[45] Davis, Fuchs, and Gertler (2014) analyze the "Cash for Coolers" program, through which the Mexican government offered subsidies to households that exchanged older, presumably inefficient, refrigerators and air conditioners for new models. They show that the program led to significantly lower energy savings than ex ante analyses had forecast.

the higher GDP growth, the estimate is still 15 percent too low. Similarly, the EIA underestimated energy demand in Brazil, a country with aggressive antipoverty programs, for 2005 by more than 25 percent. By contrast, in India, a country that has had less success than Brazil and China lifting the income of the very poor, the EIA estimate for 2005 was much closer, only low by 3 percent.[46]

Our results suggest that there will likely be a surge in the demand for energy as more and more of the households currently living in poverty benefit from overall economic development or explicit antipoverty programs and enter the middle class. Acquiring an energy-using asset for the first time leads to a considerable increase in a household's energy use. While income growth also affects energy consumption on the intensive margin, the effect is trivial compared to the effect of accumulating more energy-using assets.[47] Beyond ongoing use, acquisition of energy-using assets also induces indirect energy use through the manufacturing and distribution of the asset.[48] Investments in energy infrastructure require long lead times, so if the global demand for energy increases faster than anticipated, there could be significant shortages and increases in energy prices. In addition, country-specific energy forecasts are key inputs into projections of damages related to climate change as well as mitigation plans. Thus, it is critical to understand phenomenon like the one identified in this paper that will drive future growth in energy demand.

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[46] China, Brazil, and India are the only three countries in the developing world for which the Energy Information Administration provided country-specific forecasts.

[47] In online Appendix E, we show that Oportunidades households' electricity consumption respond very little to transfers conditional on assets.

[48] Existing work in engineering estimates "life-cycle energy estimates" to include indirect energy consumption, such as the energy used to manufacture the refrigerator and the energy embodied in the steel. For a refrigerator, existing estimates suggest that the embodied energy is about ten percent of the lifetime energy (Gonzalez, Chase, and Horowitz 2012). Given that the lifetime is more than ten years, though, the embodied energy will more than double the energy consumption in the year it is purchased.

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